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DOCUMENTED
BRIEFING

Methodologies for Analyzing Remotely Piloted Aircraft in Future Roles and Missions

Sherrill Lingel, Lance Menthe, Brien Alkire, John Gibson, Scott A. Grossman, Robert A. Guffey, Keith Henry, Lindsay D. Millard, Christopher A. Mouton, George Nacouzi, Edward Wu

Prepared for the United States Air Force

RAND PROJECT AIR FORCE

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Preface

The U.S. Air Force's remotely piloted aircraft (RPAs) have played a significant role in current operations in Southwest Asia. As the inventory of RPAs increases and new sensor technologies come online in the coming years, the Air Force has an opportunity to consider additional roles for these aircraft. Thoughtful study into these possibilities will ensure that, when the Air Force employs RPAs, they will help fill capability gaps or augment existing capabilities in more-efficient or more-effective ways.

The purpose of this documented briefing is to describe a suite of tools developed by RAND Project AIR FORCE (PAF) to help the Air Force think through future roles for RPAs. It describes tools to evaluate platform selection and concept of operations (CONOPS) development, sensor performance against various targets, weapon effects, environmental factors, platform survivability, computational processing of data, and exploitation of sensor products. This document also explains how the separate analysis in each of these areas feeds into a mission-level analysis, performed with PAF's Systems and CONOPS Operational Effectiveness Model (SCOPEM), and a campaign-level analysis using PAF's Force Structure Effectiveness (FSE) model. Use of these tools and models will help clarify how future RPAs can contribute to U.S. warfighting in cost-effective ways. The tools presented here are also useful for examining the effectiveness of new capabilities more broadly (e.g., directed energy weapons or electronic warfare capabilities); examining the effectiveness of new platforms in the context of the entire intelligence, surveillance, and reconnaissance (ISR) force posture; and evaluating the most cost-effective ISR force structure to meet future operational needs.

The model development and analytic approaches documented here should be of interest to Air Force personnel involved in future system acquisition, force structure planning, and studies and analyses. They should also be of interest to the growing RPA community within the Air Force and the intelligence officers who grapple with the increasing demands for processing, exploitation, and dissemination (PED).

The research reported here was sponsored by Randall Walden, Director for Information Dominance Programs, Office of the Assistant Secretary of the Air Force for Acquisition; Lt Gen David Deptula, then–Deputy Chief of Staff for Intelligence, Surveillance and Reconnaissance, Headquarters U.S. Air Force; and Maj Gen Thomas Andersen, then Director of Requirements, Headquarters Air Combat Command, and conducted within the Force Modernization and Employment Program of RAND Project AIR FORCE for a fiscal year 2010 study, "Developing an Analytically Based Vision for Air Force Capabilities Delivered by Remotely Piloted Aircraft." A companion report explores the suitability of RPAs to help meet capability gaps in the 2009 Air Force Capabilities Review and Risk Assessment (Lingel et al., 2011).

RAND Project AIR FORCE

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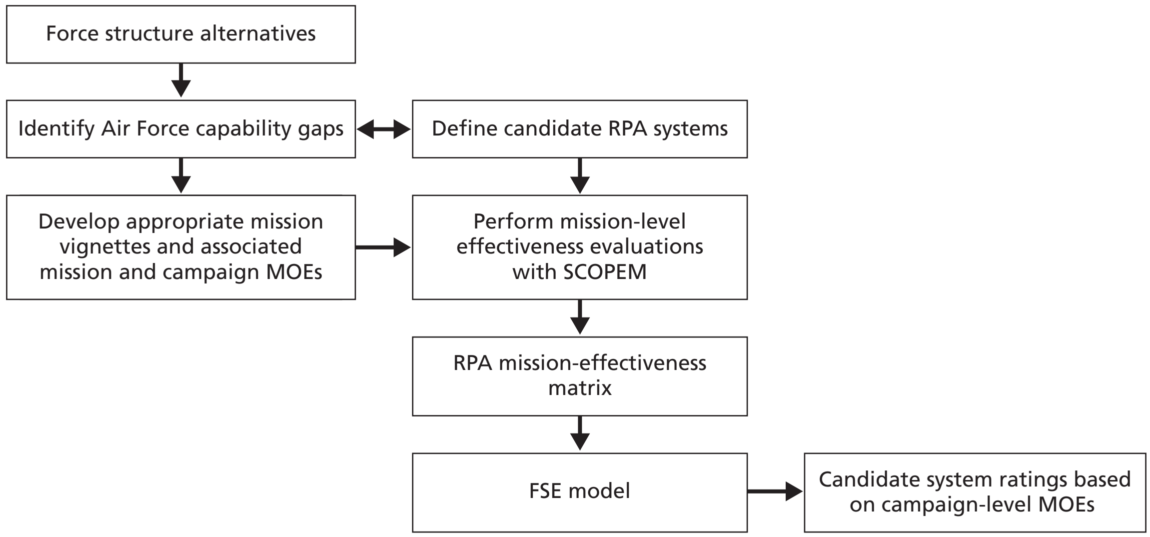
Summary

The U.S. Air Force's remotely piloted aircraft (RPAs), such as RQ-4 Global Hawk, MQ-1 Predator, and MQ-9 Reaper, have made significant contributions to current operations in Southwest Asia. Although these aircraft primarily provide intelligence, surveillance, and reconnaissance (ISR) to joint warfighters, armed variants are also able to provide rapid precision strike against time-sensitive targets. The planned increase in RPA inventories over the next several years reflects a growing awareness of the value of these aircraft. In addition, new sensor technologies, such as wide-area airborne surveillance (WAAS), will further augment RPAs' potential contribution to future warfighting.

Given these developments, the time is ripe for the Air Force to consider additional roles for future RPAs, whether to help address capability gaps that are currently unfulfilled or to replace or complement manned systems in current missions. Thoughtful study is needed to identify promising mission areas, to consider potential platform alternatives, and to analyze how different options could contribute to specific missions and to overall campaigns in cost-effective ways.

This documented briefing discusses a suite of tools and models developed by RAND Project AIR FORCE (PAF) researchers to help the Air Force think through these issues. Figure S.1 depicts the overall methodology for evaluating operational effectiveness. When analyzing alternative force structures, the first step is to identify capability gaps. Sources may include the Air Force Capabilities Review and Risk Assessment and the Multi-Service Force Deployment scenarios. The next step is to develop appropriate mission vignettes that represent a range of ways in which platforms could help fill capability gaps. Next, the trade-offs between different candidate RPAs and other systems (such as manned platforms, satellites, or ground-based systems) should be explored within a series of mission vignettes. The vignettes are selected to represent a range of potential future RPA roles under a range of conditions. Finally, the analysis results in an effectiveness matrix, which describes the conditions under which different platforms and configurations are effective. The operational effectiveness of a system can be defined as the degree to which it improves the warfighter's level of success in a given set of missions or enlarges the range of conditions under which the warfighter is likely to be successful in those missions. Operational effectiveness cannot be computed from the technical specifications of systems alone but can be observed only in terms of outcomes in an operational context that includes all the other capabilities in the theater, including space and threat systems. Because many or all of the systems being compared do not yet exist, placing the system in an operational context requires constructive simulation. Simulation further allows examination of a

Figure S.1
Remotely Piloted Aircraft Evaluation Methodology



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breadth of situations within a relatively short time frame.[1] The effectiveness matrix provides insights into the operational suitability of a given system at the mission level. In order to understand the overall force structure needed, analysis at the campaign level must occur. The result provides understanding of a candidate system's performance based on campaign-level measures of effectiveness (MOEs).

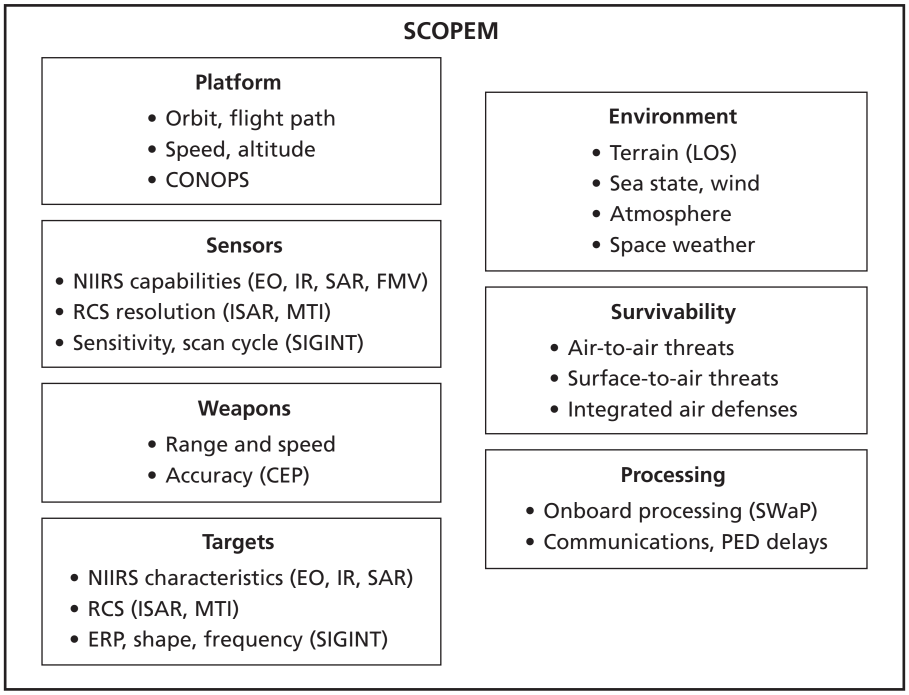
Additional entry points exist for leveraging PAF's analytic methodology. For example, alternative candidate RPAs or advanced technologies may be proposed for evaluation. In this instance, the evaluation would flow from the "Define candidate RPA systems" step to the capability-gap step in order to identify which gaps the system or technology might address. Another possibility would be evaluating force structure alternatives (based on budget constraints) in which the study objective is to assess proposed force structures and the analysis would flow to identifying the capability gaps that could arise for each. Last, analysis could start with the mission vignette step, in which the Air Force wants an assessment of the impact of a new threat capability, for example.

The models and tools used in this methodology are depicted in Figure S.2. Their purpose is to analyze the operational effectiveness and cost-effectiveness of RPAs and other candidate systems (including space systems and ground-based assets). Systems must be evaluated at the mission level first for operational effectiveness and then at the campaign level to determine overall Force Structure Effectiveness (FSE). The suite includes tools to analyze specific aspects of platforms, sensor performance against various targets, weapon effects, environmental factors, platform survivability, weapon employment, computational processing of data, and exploitation of sensor products.[2] These individual tools contribute to the mission-level analysis

[1] Constructive simulation is typically a time- or event-stepped abstraction of force-on-force operations, often employing digital terrain for analysis.

[2] The reader is referred to textbooks for sensor details, such as *Introduction to Radar Systems* by Merrill Skolnik and *Introduction to Sensor Systems* by Shahen Hovanessian.

Figure S.2
RAND's Systems and CONOPS Operational Effectiveness Model



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performed with PAF's Systems and CONOPS [concept of operations] Operational Effectiveness Model (SCOPEM). SCOPEM is structured to build a rich vignette, including terrain effects, multiple assets operating together, varied behaviors for platforms, and other features that simulate complex operational environments. The modeling occurs in simple modules of code, which provide insight into the factors that drive mission-level outcomes. MOE examples derived from SCOPEM modules include detection of a target for a sensor, line-of-sight (LOS) obscuration from terrain, and probability of kill from weapon employment. This level of detail is essential to building an effectiveness matrix, which not only identifies effective platforms and CONOPS but also defines the range of conditions under which platforms either succeed or fail at a given mission.

It is not enough to evaluate a platform's mission effectiveness to pursue a given candidate platform; one must also understand force structure implications of employing a particular RPA. To do so, we explore RPA employment at the campaign level. For example, we would like to know, for a given distribution of targets over an area of responsibility (AOR), what the effectiveness level is as a function of fleet size. A campaign scenario should include mission-level insights, as well as broader considerations, such as basing locations of RPAs and the demand frequency of mission occurrence (i.e., ground truth on target distributions in time and space). PAF has developed the FSE model to perform this campaign analysis. The campaign look afforded by FSE results in a required force size under varying effectiveness levels. The previously mentioned individual tools and the mission-level outcomes from SCOPEM inform the campaign model, FSE. Last, when the force structure evaluation is coupled with cost analysis, a cost-effectiveness examination of the candidate systems is created.

Taken together, this suite of models and tools can help the Air Force explore the most cost-effective ways to take advantage of the unique capabilities of RPAs in the future. PAF is now using SCOPEM to study a set of roles and missions for next-generation RPAs.

Acknowledgments

We would like to thank the following individuals for their contributions to this study. Natalie W. Crawford provided support, input, and guidance throughout the course of the research and generously accommodated our requests for reviews of early drafts. We are grateful to Jane Siegel for her review and preparation of this documented briefing and to Donna Mead and Jessica Bateman for the necessary administrative support to produce the briefing.

Abbreviations

AAA	antiaircraft artillery
ACC/A2	Air Combat Command Intelligence Directorate
ACC/A8	Air Combat Command Programs and Financial Management Directorate
ADA	air defense artillery
AF/A2	Air Force Intelligence Directorate
AFCCC	Air Force Combat Climatology Center
AFRL	Air Force Research Laboratory
AI	airborne interceptor
ANOPP	Aircraft Noise Prediction Program
AOR	area of responsibility
BVR	beyond visual range
C2	command and control
C3	command, control, and communications
CAP	combat air patrol
CAS	close air support
CEP	circular error probable
CFL	cleared flight level
CNR	clutter-to-noise ratio
CONOPS	concept of operations
CPU	central processing unit
CRRA	Capabilities Review and Risk Assessment
dB	decibel
dBHz	decibels relative to 1 hertz

dBJ	decibels relative to 1 joule
dBsm	decibel cross-section relative to one square meter
dBW	decibel watt
DEAD	destruction of enemy air defenses
DoD	U.S. Department of Defense
DTED	digital terrain elevation data
ECM	electronic countermeasure
ELINT	electronic intelligence
EO	electro-optical
ERP	effective radiated power
ESAMS	Enhanced Surface-to-Air Missile Simulation
EW	early warning
FDOA	frequency difference of arrival
FLOPS	floating-point operations per second
FMV	full-motion video
FOV	field of view
FSE	Force Structure Effectiveness
FY	fiscal year
GBU	guided bomb unit
GCI	ground control intercept
GFLOPS	one billion floating-point operations per second
GIQE	general image-quality equation
GMTI	ground moving target indicator
GSD	ground sample distance
HQ ACC/A8	Director of Requirements, Headquarters Air Combat Command
HQ USAF/A2	Deputy Chief of Staff for Intelligence, Surveillance and Reconnaissance, Headquarters U.S. Air Force
HSI	hyperspectral imaging
HVT	high-value target
IMINT	imagery intelligence
IR	infrared

ISAR	inverse synthetic aperture radar
ISR	intelligence, surveillance, and reconnaissance
JMEM	Joint Munitions Effectiveness Manual
LADAR	laser detection and ranging
LOS	line of sight
MC	mission capable
MGTOW	maximum gross takeoff weight
MIQE	motion imagery–quality equation
MMTI	maritime moving target indicator
MOE	measure of effectiveness
MOP	measure of performance
MOSAIC	Modeling System for the Advanced Investigation of Countermeasures
MP-RTIP	multiplatform radar technology insertion program
MSFD	Multi-Service Force Deployment
MTF	modulation transfer function
MTI	moving target indicator
MTS-B	multispectral targeting system for Predator B
NEAT	network exploratory analysis tool
NGA	National Geospatial-Intelligence Agency
NIIRS	National Imagery Interpretability Rating Scale
nmi	nautical mile
OEW	operational empty weight
PACAF	Pacific Air Forces
PAF	RAND Project AIR FORCE
PD	probability of detection
PED	processing, exploitation, and dissemination
PERL	practical extraction and reporting language
PFA	probability of false alarm
Pk	probability of kill
RADGUNS	Radar-Directed Gun Simulation

RCS	radar cross-section
RER	relative edge response
RF	radio frequency
RPA	remotely piloted aircraft
SAA	South Atlantic Anomaly
SAM	surface-to-air missile
SAR	synthetic aperture radar
SCNR	signal-to-clutter-plus-noise ratio
SCOPEM	Systems and CONOPS Operational Effectiveness Model
SEAD	suppression of enemy air defenses
SEAS	System Effectiveness Analysis Simulation
SIGINT	signals intelligence
SMC/XR	Air Force Space Command, Space and Missile Systems Center, Directorate of Developmental Planning
SNR	signal-to-noise ratio
SRTM	shuttle radar topography mission
STAP	space-time adaptive processing
SWaP	size, weight, and power
TAC	tactical air campaign
TDOA	time difference of arrival
USAF/A2	U.S. Air Force Intelligence Directorate
USAFE/A2	U.S. Air Forces in Europe Intelligence Directorate
VNIIRS	video National Imagery Interpretability Rating Scale
W	watt
WAAS	wide-area airborne surveillance
WVR	within visual range

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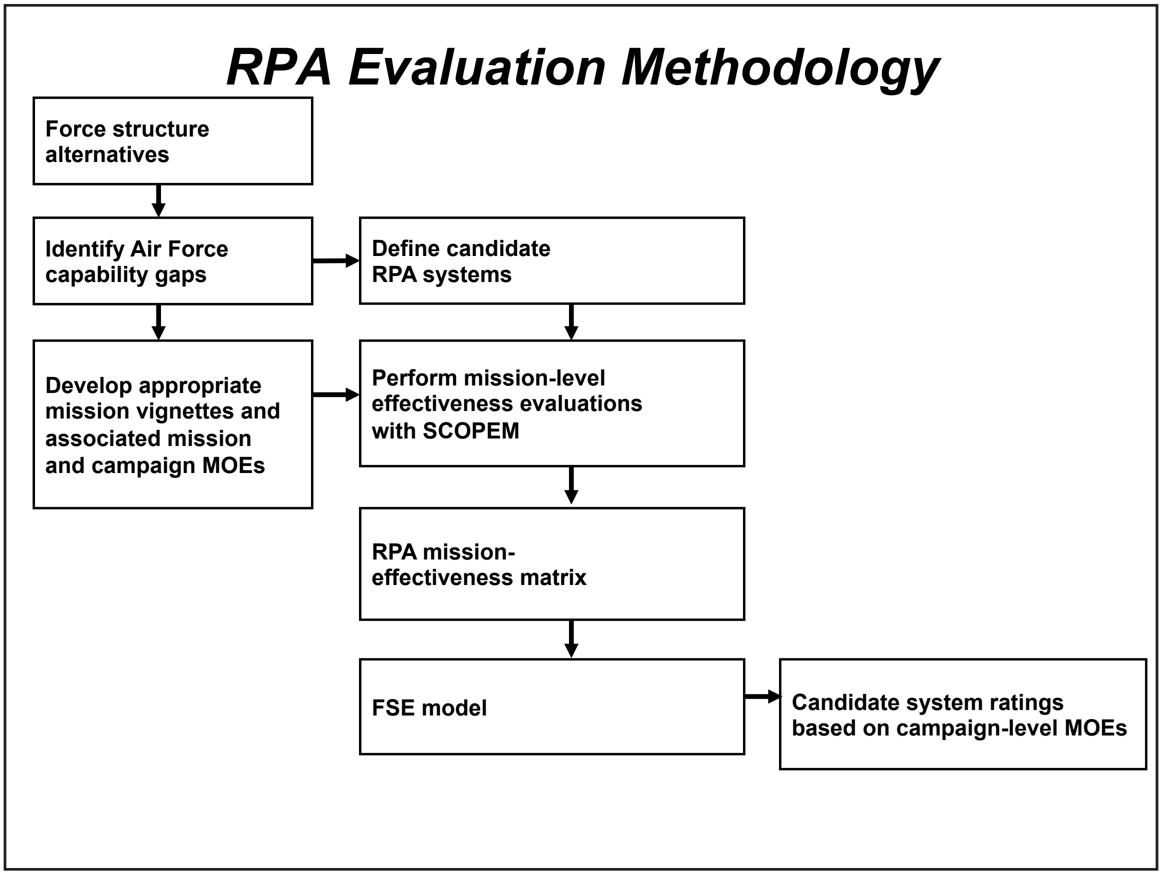
May 2011

The recent employments of remotely piloted aircraft (RPAs) in Operation Iraqi Freedom and Operation Enduring Freedom show promising expansion possibilities for RPA roles. In addition, near-term sensor technologies offer potential for new applications and concepts of operations (CONOPS) for RPAs within the next five years. These new capabilities will allow the Air Force to collect additional information on an area or target of interest, which then could be incorporated into missions with existing systems or potentially be utilized in new ways that are not realizable with current systems.

Because of these increased RPA capabilities and new sensor technologies, the environment is ripe to consider employment of RPAs in new roles. Thoughtful study into these possibilities is prudent as the Air Force explores how future systems and CONOPS can help fill capability gaps.

In this documented briefing, we describe a suite of models and tools developed by RAND Project AIR FORCE (PAF) that can contribute to this effort. All of the models developed by PAF were built within the past five years. In fiscal year (FY) 2010, some of these models were improved, and additional models were developed, e.g., the Force Structure Effectiveness (FSE) model used to determine the force size required of a given RPA candidate to meet mission objectives. Existing Air Force tools were integrated into RAND's suite of methodologies as needed. We also provide examples of model employment for evaluating candidate RPAs.



In order to explore the mission space for possible future RPA roles, a systematic analysis is followed to examine the trade-offs between the various candidate systems. This slide illustrates the analytic approach developed by PAF. The analysis of potential RPA roles begins by establishing the capability gaps or future capabilities desired for the future forces. Candidate platforms must then be defined, and subsystems for these platforms must be examined. The trade-offs between different candidate RPAs or manned platforms to fill a particular capability gap are explored within a series of mission vignettes. The vignettes, once selected, are modeled to examine the different candidate systems using RAND's mission-level analysis model, Systems and CONOPS Operational Effectiveness Model (SCOPEM). The result of analyzing the candidate systems, within the vignettes under varying conditions, is an effectiveness matrix, which shows each candidate's capabilities for a selected set of measures of effectiveness (MOEs).[1] To include the effects of conflict time in the analysis, we employ an FSE model. The candidate systems are then rated by an appropriate set of campaign-level MOEs.

Both SCOPEM and the FSE model are described in more detail later in this briefing.

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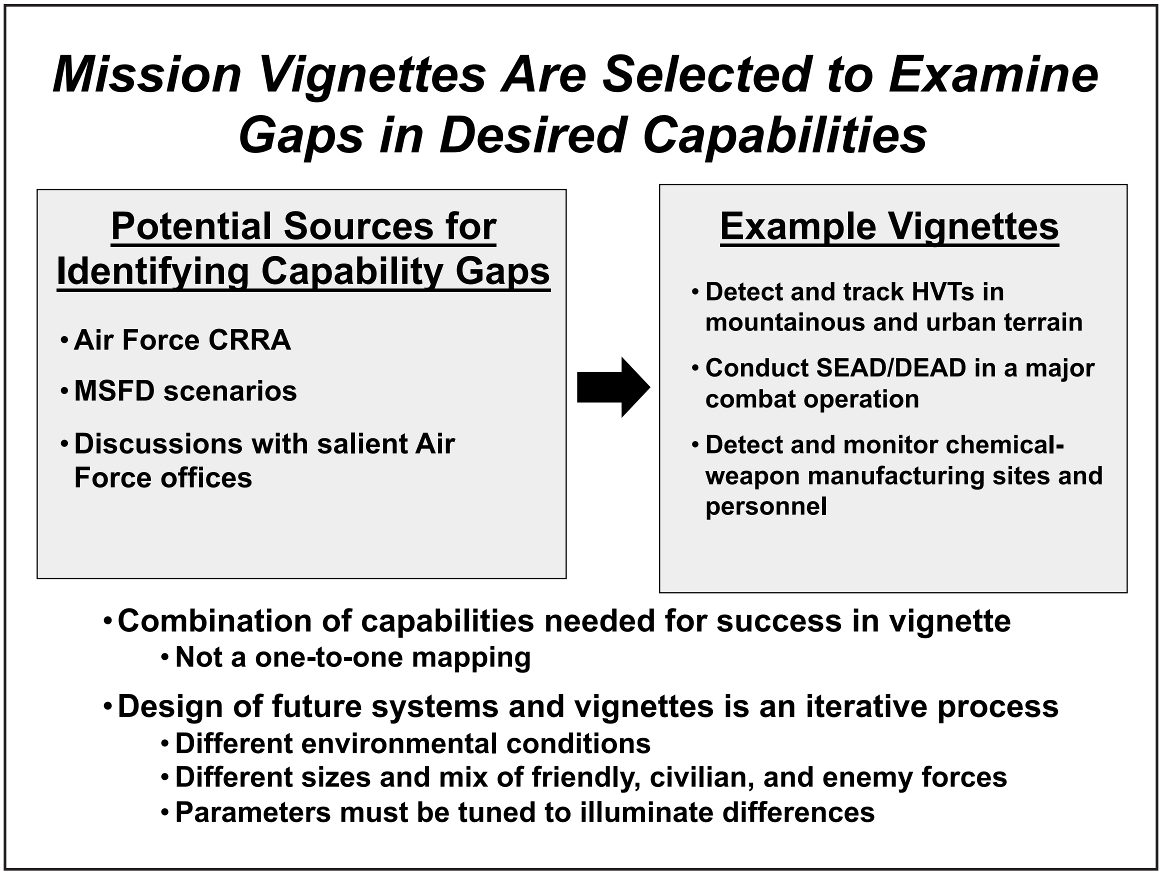
1 Measures of performance (MOPs) derived from SCOPEM modules include detection of a target for a sensor, line-of-sight (LOS) obscuration from terrain, and probability of kill (Pk) from weapon employment. Bigger-picture MOEs result from the mission-level analysis from SCOPEM, e.g., the candidate platform successfully tracked the vehicle for 30 minutes.



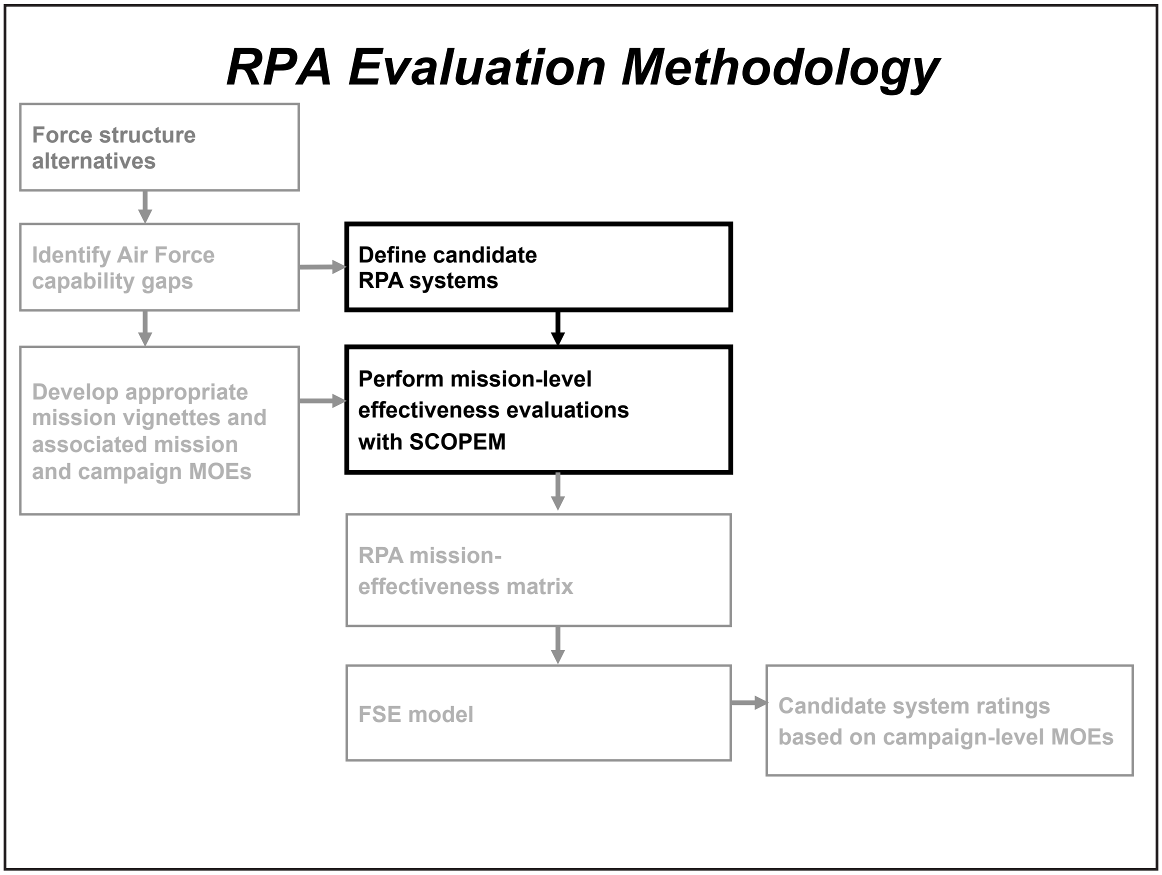
To explore future roles and missions of RPAs, it is useful to determine U.S. Air Force capability gaps that could potentially be met by RPA platforms. Vignettes are useful to shed light on the mission effectiveness of one candidate versus another under varying environmental conditions.

There are several potential sources for establishing capability gaps. One may refer to the Air Force Capabilities Review and Risk Assessment (CRRA) to include in the analysis the Air Force's stated capability gaps. Referencing the Multi-Service Force Deployment (MSFD) scenarios gives a joint perspective on mission needs for future force structure planning. Discussions with salient Air Force offices concerning particular mission areas are another source for finding capability gaps.

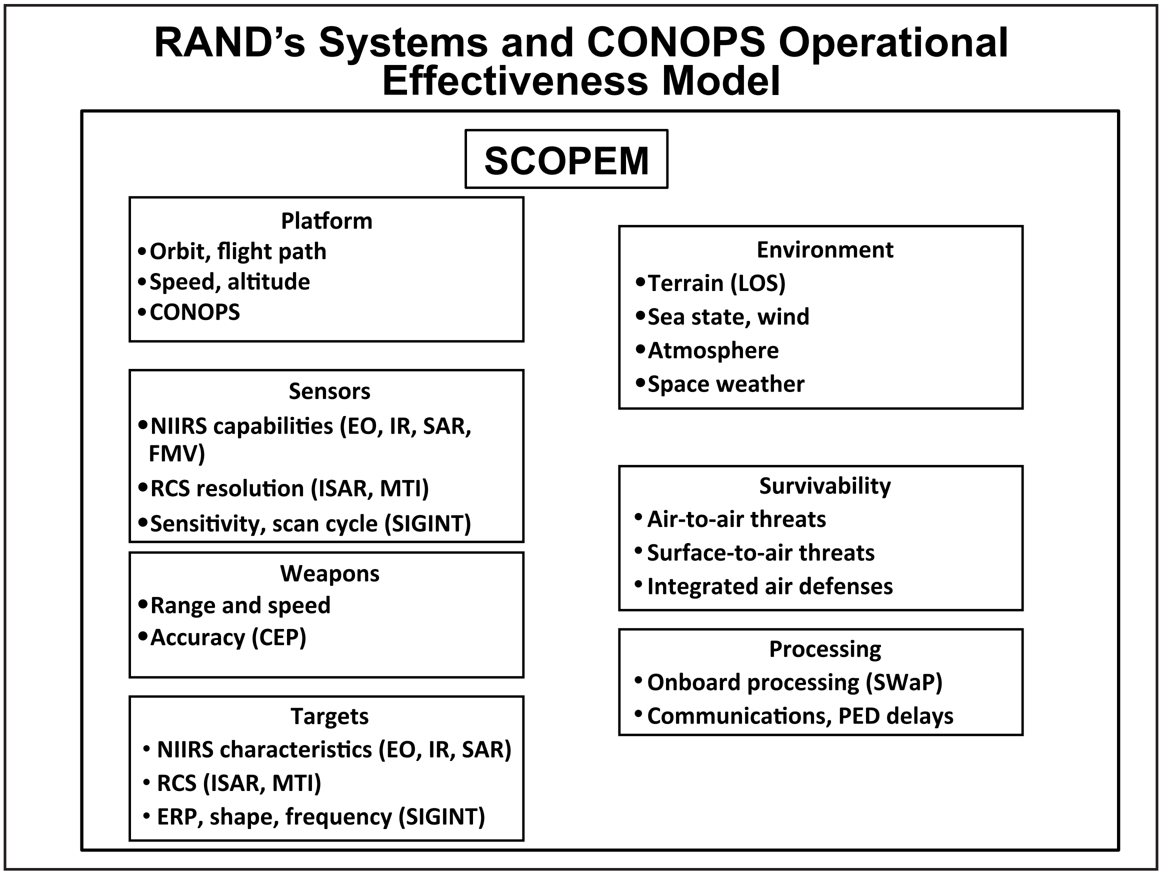
Once the desired capabilities are established, a set of vignettes is selected to evaluate the candidate systems within these situations and determine their mission effectiveness. Note that it often takes multiple capabilities to successfully complete a mission within a vignette. For example, detecting and tracking a high-value target (HVT) in mountainous or urban terrain require the capabilities of persistence, observing targets in challenging terrain, and maintaining track of individuals. Conducting suppression of enemy air defenses (SEAD) and destruction of enemy air defenses (DEAD) in a major combat operation requires detection of emitting radars, high-resolution imaging and accurate geolocation of air defenses, penetrating a denied environment and surviving, and effectively employing weapons to destroy the target. Therefore, a simple one-to-one mapping between capability and vignette does not exist; rather, there is a more complex relationship between the two.

The design of future candidate systems and vignettes within which they are examined is an iterative process. Analysis must cover different environmental conditions, threats, and sizes

and mixes of forces. In varying these parameters, the differences among candidate systems and CONOPS are illuminated.



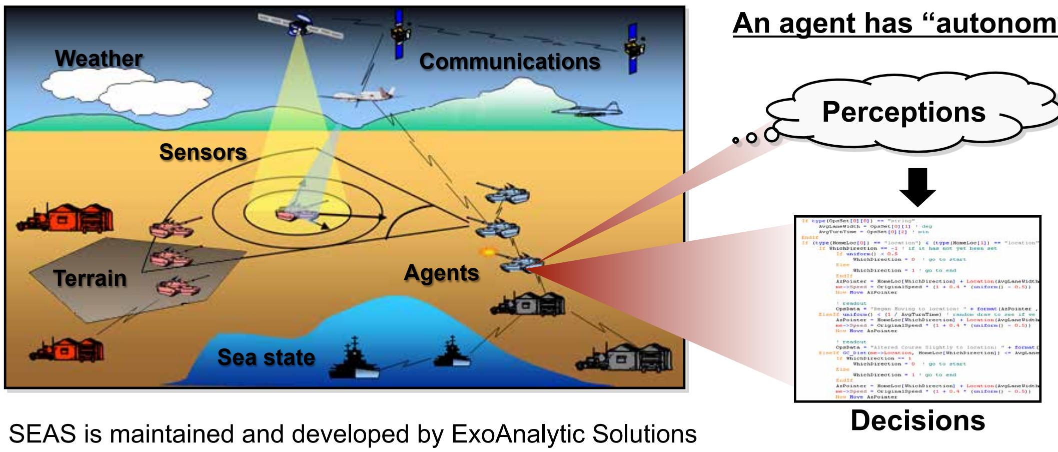
Mission-level analysis provides a framework within which candidate systems can be evaluated. Three areas of analysis fall within this category: candidate platform development and selection, subsystem modeling, and simulations of systems and CONOPS within vignettes. In the following slides, we discuss the tools and models we have developed that contribute to this analysis and how they relate to one another.



There are many factors that affect operational effectiveness of a candidate system; in this documented briefing, we describe the tools that PAF uses to evaluate those influences. We now present our mission-level model, which integrates these factors and permits analysis of mission-level effectiveness.

Once mission- or vignette-level analysis is complete, the analyst has an understanding of the type and number of RPAs that are needed to perform a particular mission within a vignette. But, how does this transfer to how many platforms are needed for a force size of that RPA system? A higher-level trade analysis model could be used to explore the overall force structure requirements and associated costs of a given candidate system. PAF has developed a model, the FSE model, to aid in this analysis, too.

SEAS/SCOPEM Is an Agent-Based, Time-Stepped, Stochastic Modeling Environment



SEAS is maintained and developed by ExoAnalytic Solutions for SMC/XR. SEAS is part of the Air Force Standard Analysis Toolkit and the Air Force Space Command Modeling and Simulation Toolkit.

SCOPEM, originally named by RAND the Collection Operations Model, is a suite of integrated modules written for the System Effectiveness Analysis Simulation (SEAS) modeling environment. SEAS is an agent-based representation of operations that proceeds in discrete time steps, usually ranging from one second to one minute. Each agent has a measure of autonomy, meaning that it makes decisions based on its perceptions, as dictated by the sensors and environment.[2] RAND has added a large number of new properties and complex decision rules that allow SCOPEM to evaluate operations in a considerably more comprehensive manner than SEAS alone (e.g., detecting a target with one sensor and cuing a second sensor or platform to track or attack it). Since it was initiated in 2005, SCOPEM has supported a variety of studies, including the following:

- "Non-Traditional Intelligence, Surveillance, and Reconnaissance" (FY 2008–2009, Jody Jacobs, Bart Bennett; sponsored by U.S. Air Force Intelligence Directorate [USAF/A2])
- "Satisfying the Demand for Surveillance and Reconnaissance in the European and African Theaters" (FY 2008, Carl Rhodes; sponsored by USAF/A2 and U.S. Air Forces in Europe Intelligence Directorate [USAFE/A2])
- "The Role of Global Hawk in Maritime Surveillance" (FY 2006–2007; Sherrill Lingel, Carl Rhodes; sponsored by Pacific Air Forces Intelligence Directorate [PACAF/A2], AF/A2, Air Combat Command Intelligence Directorate [ACC/A2], and Air Combat Command Programs and Financial Management Directorate [ACC/A8])

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[2] Satellites are represented in SCOPEM as modeled by the government in SEAS.

- "Tasking and Employing USAF Intelligence, Surveillance, and Reconnaissance Assets to Support Effects-Based Operations" (FY 2005–2006; Sherrill Lingel, Carl Rhodes; sponsored by PACAF/A2).

Many of the more-recent improvements to SCOPEM have been designed to allow more-detailed analysis of Air Force RPAs. The following slides discuss how SCOPEM may be used to support future work in this area.

Because vignettes may have very different measures of effectiveness associated with them—and these measures may be refined as the vignette is developed—the simulation should be able to provide flexible output. SCOPEM provides three main options.

The most common form of output from SCOPEM is a report of every detection by every sensor on every time step. (Filters can be applied to limit attention to particular sensor/target combinations as needed.) Along with the detection, the model reports perceived target parameters, such as location and velocity (with uncertainties), and reports approximate measures of the quality of the detection (e.g., National Imagery Interpretability Rating Scale [NIIRS] rating, signal-to-noise ratio [SNR]). These statistics can be compiled and processed afterward, e.g., in a spreadsheet, to generate MOEs. In addition, the model also reports any targets within range that were not detected. This allows the analyst to explore which factors prevented the detection. Note that these data are reported for the output only and are not used within the simulation. Agents are never permitted to peek at ground truth.

Another option, often used, is the ability to design customized output of any parameter that can be calculated during run time in SCOPEM. In many cases, the general reporting above is used until the particular features that are needed can be identified, at which point a custom routine is written to write out only those parameters.

A third option is to use the standard output files of SEAS itself. Because SCOPEM relies on several dozen parameters that RAND has added to SEAS, the standard output file does not report these. However, it provides basic information regarding sensor detections and weapon fire. This can also be used diagnostically.

Measuring the Operational Effectiveness of a Future System Involves Several Fundamental Challenges

- **Effectiveness can be measured only in terms of outcomes in an operational context**
  - **Effectiveness is how much the system helps the warfighter achieve the operational objective.**
  - **Effectiveness cannot be computed from technical specifications alone.**
  - **A large trade space of qualitatively different capabilities exists.**
- **Whole may be greater or lesser than sum of its parts**
  - **Must be evaluated in light of its contribution to (or reliance on) the capabilities of the entire force**
- **Future systems do not yet exist**
  - **CONOPS for using system may be new, untested**
  - **Simulations depend on models of enemy behavior**

The operational effectiveness of a system is, in essence, the degree to which it assists the warfighter. More specifically, it can be defined as the degree to which the system improves the warfighter's level of success in a given set of missions or enlarges the range of conditions under which the warfighter is likely to be successful in those missions. These benefits cannot generally be computed from the technical specifications of the system alone. They can be observed only in terms of outcomes in an operational context that includes all the other capabilities in the theater, including space and threat systems. Because the system does not yet exist, placing the system in operational context requires constructive simulation.

Measuring the operational effectiveness of a future system therefore entails many difficulties. First, the set of missions over which the system will be judged—and the range of environmental conditions considered—must be agreed upon by the stakeholders. Otherwise, the mission-level analysis, no matter how sophisticated, will be decidedly less useful to the decisionmaker. Second, the system cannot be fairly judged in isolation. It must be evaluated in light of its contribution to—or reliance on—the capabilities of the rest of the force. Moreover, many systems can be expected to provide several different capabilities, and the contributions of one might depend on the others. The set of missions must be rich enough to support those interactions without becoming so complicated that the effect of the new system becomes too subtle to discern. Third, CONOPS for using the new system might be new, and the tactics might be untested or may not yet exist. Finally, the models of enemy behavior (on which the results depend) might be highly speculative.

These difficulties are challenging and favor certain simulation methods. Clearly, any model used needs to be very flexible, able to simulate different "players" in a wide range of sce-

narios under many different environment conditions. More important, however, is the level of resolution of the model. Unlike engineering simulations, a model for operational effectiveness should be geared toward representing many features at lower fidelity, rather than a few features at high fidelity.[3] This is driven by the challenges described above.

Simply put, there is much uncertainty in simulating operational employment, and this should be acknowledged at the outset. That the final results could depend heavily on predictions of enemy behavior should, by itself, be enough to give one pause. There is nothing to be gained (and much to be wasted) by simulating some aspects to high precision, such as sensor systems or environmental characteristics, when many others must be simplified. We must remember that the purpose of this modeling effort is to assist decisionmaking. In some situations, it might be that all we can reliably conclude is that the comparative effectiveness of two systems depends strongly on factors we cannot predict. That statement has more value to the decisionmaker than a highly detailed prediction that is ultimately based on questionable assumptions.

The ultimate goal of operational effectiveness analysis at the mission level is to allow the analyst to trace the modeling results back to the root causes of success or failure for any given alternative. For example, was there an environmental condition that prevented the sensor from detecting a target? Or, did the CONOPS employed limit the sensor's field of regard of the target such that changing the orbit location would bring mission success? The results must be accessible to the analyst and explainable to the decisionmaker in order to be credible. SCOPEM, along with the associated suite of tools, provides these capabilities to the analyst.

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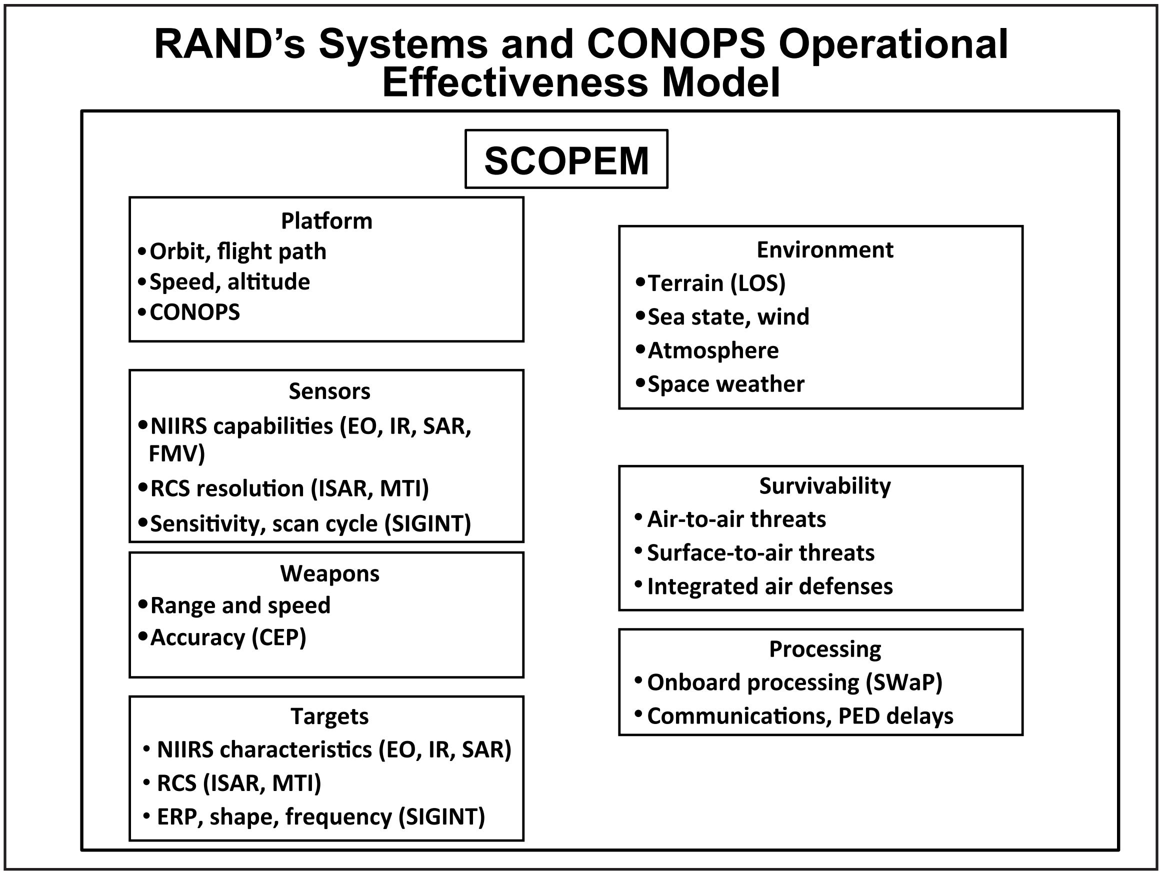
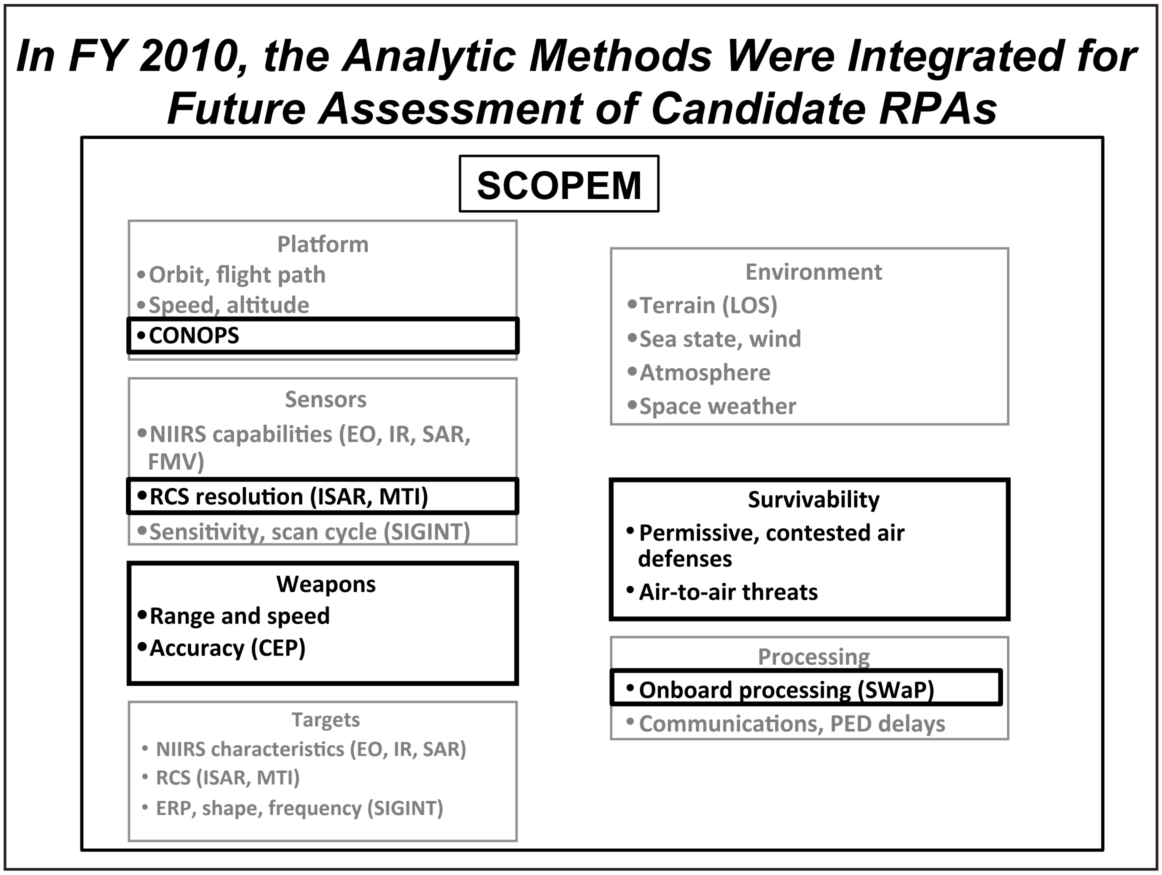
[3] An engineering simulation can model subsystem parts with high fidelity but not characterize the operational impact of those systems.

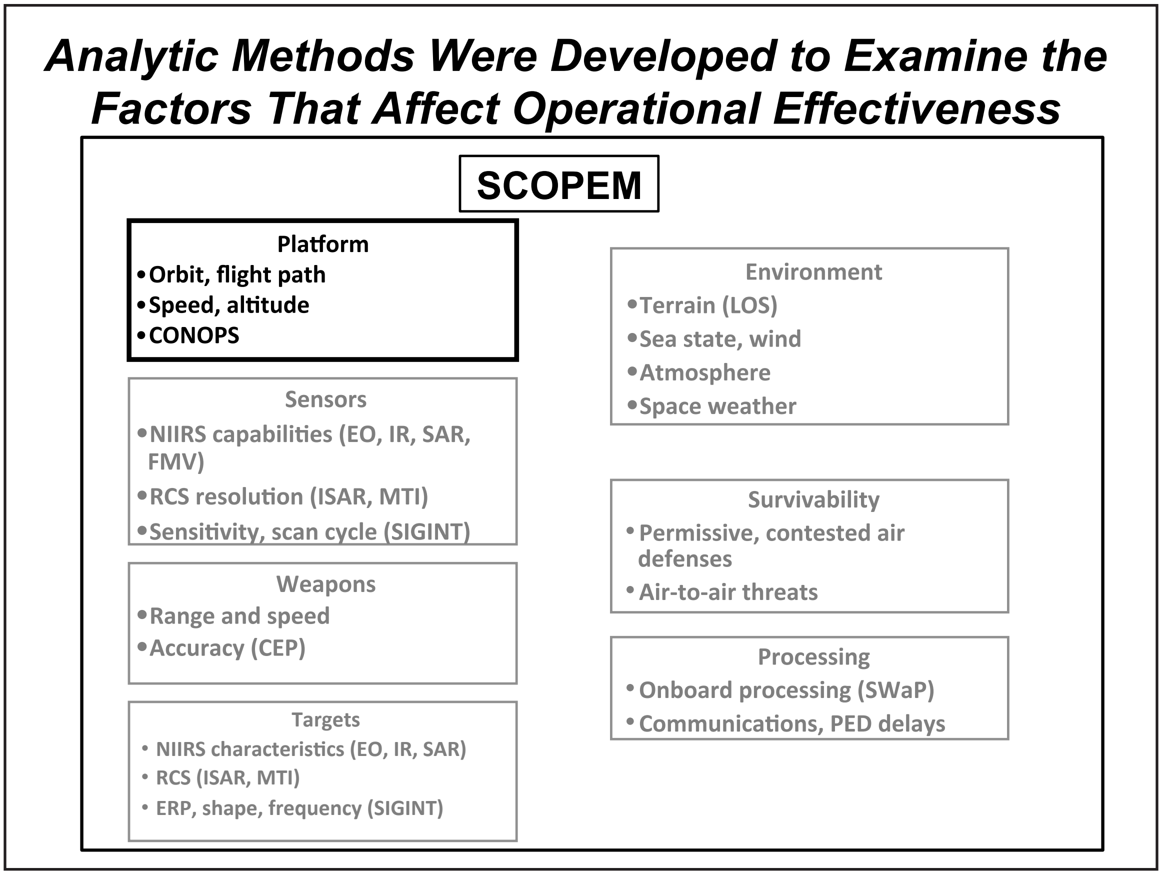


In this section, we take a closer look at SCOPEM and discuss individual modules in more detail. The SEAS/SCOPEM environment includes elements of the platform, environment, sensor, targets, and processing modules. Survivability and weapon employment model outputs provide data for the mission-level modeling in SCOPEM.



The suite of analytic methods described above and detailed in the following pages are not limited to RPA analysis but are applicable across manned airborne, RPA, space, and ground-based systems. Some of the methods make use of existing U.S. Department of Defense (DoD) resources, such as the aircraft survivability model Enhanced Surface-to-Air Missile Simulation (ESAMS) or the Joint Munitions Effectiveness Manual (JMEM) weapon employment model. Others are previously developed RAND tools. All have been integrated into a unique suite that is designed to evaluate RPAs in a range of missions. The highlighted portions in this slide represent the methods that were modified and developed for the PAF effort in FY 2010.

The following slides detail individual analytic methods in the areas of platform, sensors, weapons, targets, environment, survivability, and processing, as well as SCOPEM, which performs mission-level analysis, and the FSE model, which performs campaign-level analysis.



We apply a systematic approach to defining candidate manned and unmanned systems and develop appropriate employment concepts for each tailored to the mission undertaken. The next set of slides describes our approach to selecting platforms and assessing suitable CONOPS to be evaluated within our mission-level analysis.

First Candidate Platforms and CONOPS for Employing Them Are Defined

- **Developing preliminary RPA performance specifications is an iterative process**
  - **May include trade analyses between platform and payload requirements**
- **The parameters considered in the RPA performance depend on the mission and may include the following:**
  - **Platform: Dash and loiter speed, maximum altitude, endurance, maneuverability, survivability (e.g., signature, active defenses), size of platform, SWaP capacity, processing and communications capabilities**
  - **Payload: SWaP requirements, active/passive, detection range, resolution, FOV, measurement quality (e.g., NIIRS), agility, processing capability, communications requirements**

We first define candidate RPA or manned platforms and work with the Air Force to develop CONOPS for employing them. Based on the mission objectives, the platform constraints, and the terrain and threat environments, we develop preliminary platform performance specifications. Establishing specifications is an iterative process that may include a trade analysis between the platform and the payload requirements. The first iteration begins with the operational need. From that need, we work with subject-matter experts to develop a first set of platform characteristics.

The RPA platform characteristics under consideration may include dash and loiter speed, maximum altitude, endurance, maneuverability, survivability (e.g., signature reduction and active defenses), payload size, weight, and power (SWaP) capacity, and processing and communications capabilities.

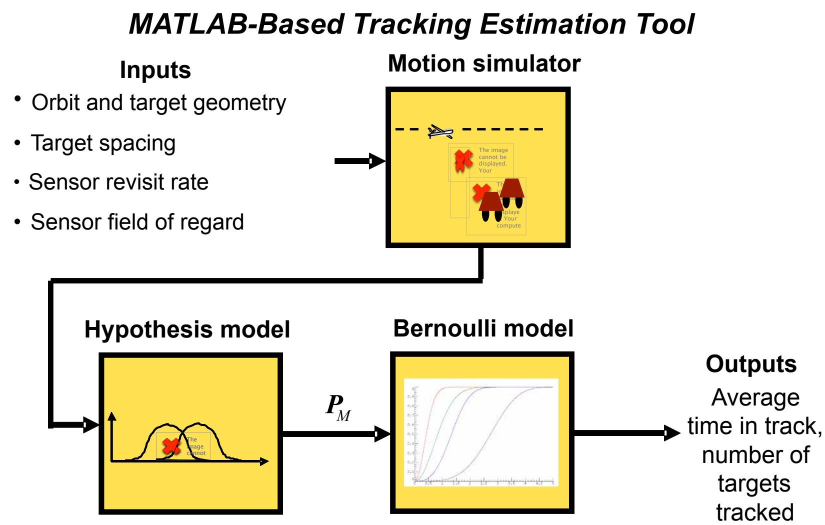
Payload characteristics include SWaP and communications requirements. Additional characteristics for sensor payloads may include active or passive sensors or both, detection range, resolution, field of view (FOV), measurement quality (NIIRS), agility, and processing requirements.

Sensor performance is analyzed separately, as discussed later in this documented briefing. If sensor performance results fail to meet mission requirements, then an iterative process in which the system architecture is refined and reevaluated is conducted to obtain an acceptable initial architecture.

Trades between the number of RPAs and their platform and payload performance parameters are also included in the approach, as is discussed in this document. The process will

include sensitivity analysis to evaluate the impact of performance requirements, related technology maturity, and risks (and cost) on overall mission performance.

PAF's Tracking Estimation Tool Helps Identify Orbits for Surveillance

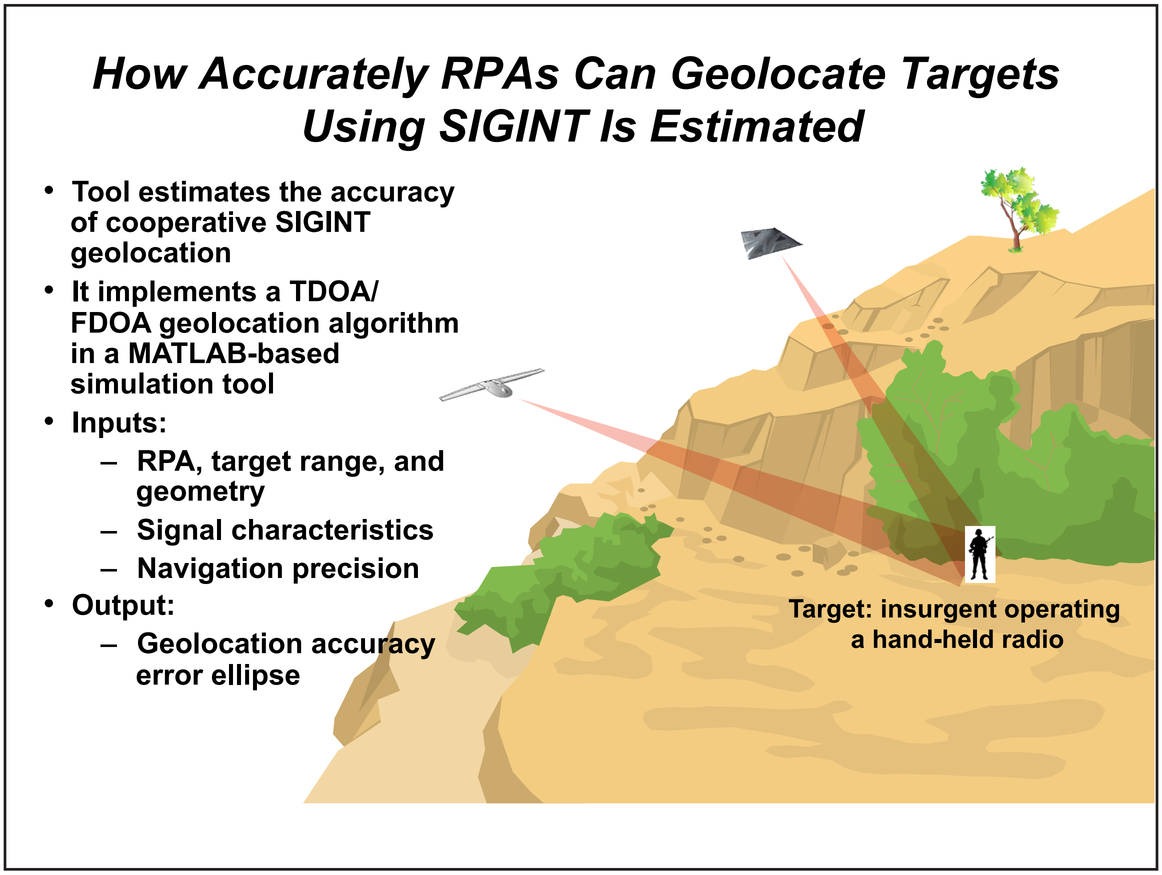


We use the tool to identify the best orbits for tracking targets and implement these orbits in SCOPEM.

An appropriate CONOPS for each mission must be developed along with each candidate RPA or manned platform. Sources for candidate CONOPS include warfighter tactics, techniques, and procedure documents and direct warfighter input. For intelligence, surveillance, and reconnaissance (ISR) missions, an important aspect of this CONOPS is the flight pattern or orbit for the platform. Our tracking estimation tool helps identify orbits for surveillance missions by providing MOEs. Increased average time for which a target is tracked and maximum number of targets that can be tracked are two examples of MOEs. Flight paths are also important for survivability concerns in contested environments but are not considered within this tool; instead, they are considered in the larger mission-effectiveness model.

The tracking estimation tool consists of three interconnected models, as shown in the slide. The primary inputs to the tool include information about the sensor platform orbit and target geometry, the average spacing of the targets with respect to each other, the sensor revisit rate (how often the sensor sweeps over the target), and the sensor field-of-regard specifications. These inputs feed into a motion simulator model that updates the position of the sensor platform along its orbit and the position of the target along its path during a sequence of time steps. The output is then fed into the hypothesis model, which estimates the probability that track of the target will be maintained between subsequent revisits of the sensor. It does this by evaluating the probability that a position measurement of another target may be confused with that of the target. This probability is then passed to the Bernoulli model, which accumulates the outputs of the hypothesis model to determine the aggregate probability distribution of maintaining track as a function of total elapsed time since the track was established.

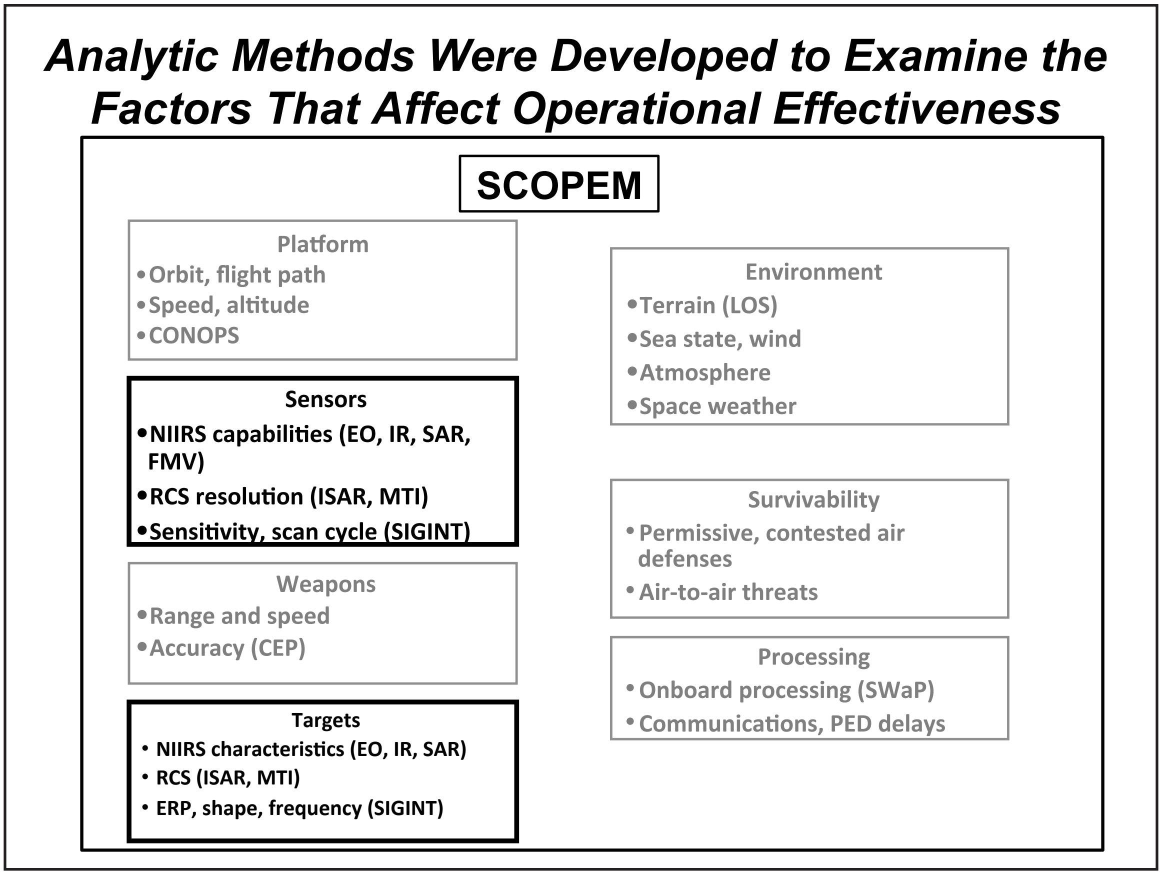
The tracking estimation tool can be used to identify the best surveillance orbits for RPAs to use during tracking missions. These orbits are incorporated into simulation tools, such as SCOPEM.



Another factor that may influence CONOPS and sensor selection for ISR missions is a candidate platform's ability to geolocate a target from its electronic emissions. We developed a tool to estimate how accurately candidate platforms can geolocate an emitting target. Although some platforms can perform direction finding themselves, the accuracy is poor, and multiple platforms operating together would improve accuracy. For example, two platforms will receive these electronic emissions at slightly different times (assuming they are at different ranges from the target). Hence, there will be a time difference of arrival (TDOA). Similarly, there will be a frequency difference of arrival (FDOA) due to Doppler shift created by the motion of the platforms. The source of these electronic emissions can be located as the intersection of TDOA and FDOA contours on the earth's surface. We implemented this TDOA/FDOA geolocation technique in a MATLAB simulation tool. Inputs to the tool include platform and target position and velocity, characteristics of the emitted signals and receiving electronics on the platforms, and accuracy of the platform navigation systems. Inferred in this analysis are the platforms' flight paths relative to the target. The output of the tool is the predicted geolocation accuracy. The tool can be used to determine platform sensor requirements for targeting, suitable flight paths, and other mission tasks.

Geolocating targets based on signals intelligence (SIGINT) collections can be used as a means of cuing additional surveillance sensors on the target. For example, within SCOPEM, when a target is geolocated with TDOA or FDOA, an area on the ground is provided (the geolocation error ellipse) of where the target could be located and where we may want to collect imagery as a directed search. Electro-optical/infrared (EO/IR) or full-motion video (FMV)

sensors may then be tasked to image the area to identify the target and provide a more accurate location.



We have developed a suite of models to calculate MOEs for many types of ISR sensors. These ISR sensors may reside on RPAs, manned platforms, or satellites. Together, these provide SCOPEM with a means of evaluating how specific platforms perform ISR collections against specific targets under various environmental conditions. The following slides describe our methodologies for analyzing EO/IR, FMV, wide-area airborne surveillance (WAAS), ground moving target indicator (GMTI), synthetic aperture radar (SAR), and electronic intelligence (ELINT) sensor performance.

EO/IR NIIRS as a Function of Range Is Determined from Contractor Data and the GIQE

- A contractor or program office may supply NIIRS as a function of range for sensors already fielded or under development.
- When NIIRS data are not available, the GIQE is used to estimate performance.

$$NIIRS_{EO} = 10.251 - a\log_{10}(GSD_{GM}) + b\log_{10}(RER_{GM}) - 0.656H - \frac{0.344G}{SNR}$$

GSD_{GM} : GSD based on sensor FOV, platform orientation, and range
SNR : SNR based on target type, atmosphere, weather, and internal sensor noise
RER_{GM} : Normalized RER based on pixel density
H, G : Respectively, mean-height overshoot and noise gain, measures of the effect of MTF compensation

- SCOPEM uses NIIRS data to calculate MOEs
  - NIIRS performance curves for all EO/IR sensors are provided to SCOPEM.
  - Military and civilian NIIRS tables define the NIIRS level required to detect, classify, or identify a target.
  - SCOPEM determines the probability of detecting, classifying, or identifying targets in diverse scenarios.

For ISR-related capabilities, one MOE may be a sensor's ability to detect or identify a target. The MOEs for EO and IR sensors are defined as the probabilities of detecting, classifying, and identifying objects of interest in varying scenarios.

The ability of an EO/IR sensor to detect and identify a target may be quantified using the NIIRS. NIIRS level is a measure of the interpretable content of an image, based on the empirical performance of experienced analysts. Table 1 shows the NIIRS level necessary to detect and

Table 1
National Imagery Interpretability Rating Scale Necessary to Detect or Identify Notional Targets

	EO NIIRS		IR NIIRS	
Target	**Detect**	**Identify**	**Detect**	**Identify**
Group of trucks	4	6	4	6
Truck	4	6	4	6
Motorcycle	5	6	5	7
Group of people	6	8	7	8
Person	6	8	7	9
Person with weapon	7	8	8	9

SOURCE: Imagery Resolution Assessments and Reporting Standards Committee, 1996.

identify various target types. These estimates are a subset of much larger military and civilian NIIRS tables developed by the U.S. government.

The NIIRS approach accounts for many factors that affect image interpretability, including sensor resolution, image sharpness, noise, contrast, and human effectiveness at interpreting the image. However, NIIRS does not include effects of foliage, camouflage, clouds, or other objects that may obstruct the view of a sensor.

NIIRS level, as a function of range, is often obtained via hardware testing by sensor contractors. However, NIIRS level may also be estimated using the general image-quality equation (GIQE).[4] The GIQE is a model to predict NIIRS level based on sensor, target, and environmental characteristics (Leachtenauer and Driggers, 2001, p. 301). Target effects (aspect, size, contrast) are captured in the ground sample distance (GSD) term and, potentially, the SNR ratio term. Atmospheric effects and weather are included via the SNR term. Sensor characteristics define the GSD and modulation transfer function (MTF)–related (relative edge response [RER]), and to a lesser degree, *H* and *G* terms. This version of the GIQE assumes that hardcopy imagery is being exploited. Also, any degradation due to image compression is ignored.

NIIRS performance results are used to examine the performance of a given sensor to collect on a particular target. When evaluating the candidate platform performance in a vignette, SCOPEM must test, at each time step over the duration of a mission, whether a platform (with a defined EO/IR sensor package) is able to attain an adequate NIIRS level to detect, classify, or identify a target. Using Monte Carlo analysis, SCOPEM provides the probability of detecting, classifying, and identifying a target, as well as the EO/IR sensor's impact on overall mission success.

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4 In the GIQE, a and b are constants; when defined, $a = 3.32$ if RER ≥ 0.9 or 3.16 if RER < 0.9, and $b = 1.559$ if RER ≥ 0.9 or 2.817 if RER < 0.9.

Performance of Motion Video and WAAS Sensors Is Modeled by Leveraging NIIRS Analysis

- **EO/IR GIQE and NIIRS tables for *still* imagery are used to qualitatively approximate the intelligence value of *motion* imagery**
  - **VNIIRS has recently been accepted by the Motion Imagery Standards Board**
  - **However, developing the associated MIQE is still an active area of research (i.e., one has not been fully developed and accepted)**
- **To simulate motion imagery, images are taken contiguously—at each time step—in SCOPEM**
  - **This results in the achievable NIIRS level as a function of time for each sensor in each scenario**
  - **NIIRS level as a function of time is used to determine probability of detection, classification, identification, and maintaining track**
- **SCOPEM includes initial Gorgon Stare WAAS CONOPS**

The EO/IR GIQE and NIIRS tables for still imagery are used to approximate the interpretability of motion imagery. Although a video NIIRS (VNIIRS) has recently been accepted by the National Geospatial-Intelligence Agency (NGA) as a subjective quality scale for rating the intelligence value of airborne motion imagery in the visible spectrum, developing the associated motion imagery–quality equation (MIQE) is still an area of active research (Motion Imagery Standards Board, 2009; Young and Bakir, 2009). Because the MIQE is not yet verified, the GIQE and still-imagery NIIRS are used to evaluate FMV sensor performance in SCOPEM.

Motion imagery is simulated as a series of still images. This results in the achievable NIIRS level as a function of time for each EO/IR FMV sensor in each scenario. NIIRS level as a function of time may be used to determine the probability of detecting, classifying, and identifying a target in the same way as previously described for still imagery.

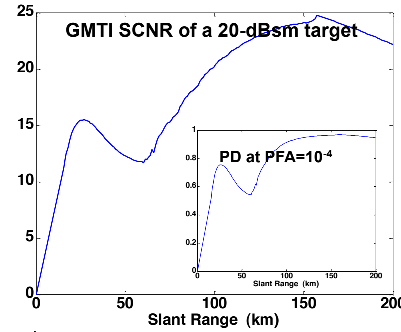
SCOPEM also simulates an EO/IR FMV sensor's ability to track a target of interest. The ability to track a target with FMV will be a function of the sensor's ability to maintain a target in view, at a specified NIIRS level. In environments without traffic, the sensor must maintain a NIIRS level above that required to *detect* the object. In high-traffic scenarios, the sensor must have a NIIRS level above that required to *identify* the target in order to distinguish it from nearby "confusers." The sensor can lose track of the target for periods of time during a scenario. Thus, the probability of track is defined as the average percentage of time that a target is both within the sensor FOV and at the required NIIRS level.

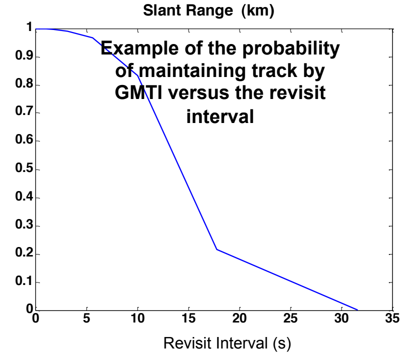
One example of an EO/IR FMV capability currently modeled in the SCOPEM environment is the WAAS Gorgon Stare. In the current design, Gorgon Stare contains five black-and-white EO cameras, as well as four IR cameras. A relatively seamless view is produced from

each of the cameras (within each bandwidth) via stitching algorithms; this provides approximately 12 square kilometers of coverage on the ground in the sensor FOV at any time. Current Gorgon Stare CONOPS require the associated platform to stay at a constant altitude during sensor operations, implying a constant attainable maximum NIIRS level (Prociuk, 2009).

The GMTI/Tracking Model Allows SCOPEM to Compute Probabilities of Detection and Maintaining Track

- **PD of moving targets**
  - **Based on physical radar, target, and clutter characteristics**
  - **Predicts signal and clutter energy received by the radar**
- **Probability of maintaining track**
- **Revisit interval incorporates sensor, target, and environmental characteristics**
  - **Based on a model by Mori, Chang, and Chong***
  - **The GMTI detection model results in estimates of target SCNR and PD**
  - **The tracking model results in the probability of maintaining track on a target of a given SCNR within SCOPEM**





* Mori, Chang, and Chong, 1992.

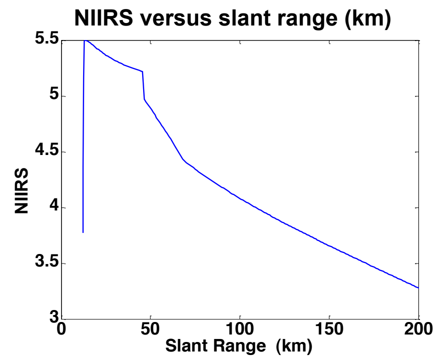
Maintaining track of a mobile target is important for many ISR missions. PAF developed three tools to address different aspects of tracking. Earlier, we presented our tracking estimation tool that helps identify suitable orbits based on the vehicle traffic density, the target's motion uncertainties, and the geometry between the sensing platform and the target. We also discussed tracking with FMV, in which the "tracking" uses the human eye or analysis software. Tracking moving targets using GMTI radar is another way to track targets, and PAF's GMTI/tracking model is our third model related to tracking. This model computes the probability of detection (PD) and maintaining track of a target and includes the effects of background clutter on detecting a moving target.

Under appropriate simplifying assumptions, PD is related to signal-to-clutter-plus-noise ratio (SCNR) and the probability of a false alarm (PFA) by a simple expression. The inset to this slide shows PD versus slant range.

The probability of maintaining track versus the revisit interval incorporates sensor, target, and environmental characteristics. The model has been implemented in SCOPEM as tables of probabilities of maintaining track for a range of revisit intervals, target orientations, and SCNRs at a set of reference values that includes the target density at each time step. Details of the GMTI model implementation are described in "Additional Detail on Selected Models" at the end of this briefing.

The SAR Model Predicts Detection or Classification Based on Exceeding Threshold NIIRS Values

- **The SAR model uses the SAR GIQE for NIIRS but modified to use an "effective" resolution versus grazing angle that depends on target dimensions and accounts for the effects of**
  - **Differing resolution on horizontal and vertical surfaces**
  - **Grazing dependence of RCS of corner reflectors**
  - **Shadowing**
- **SCOPEM uses this model to predict the potential to detect or classify targets by SAR**
  - **NIIRS thresholds are specific to target types**



Example shows loss of image quality at very high and low grazing angles

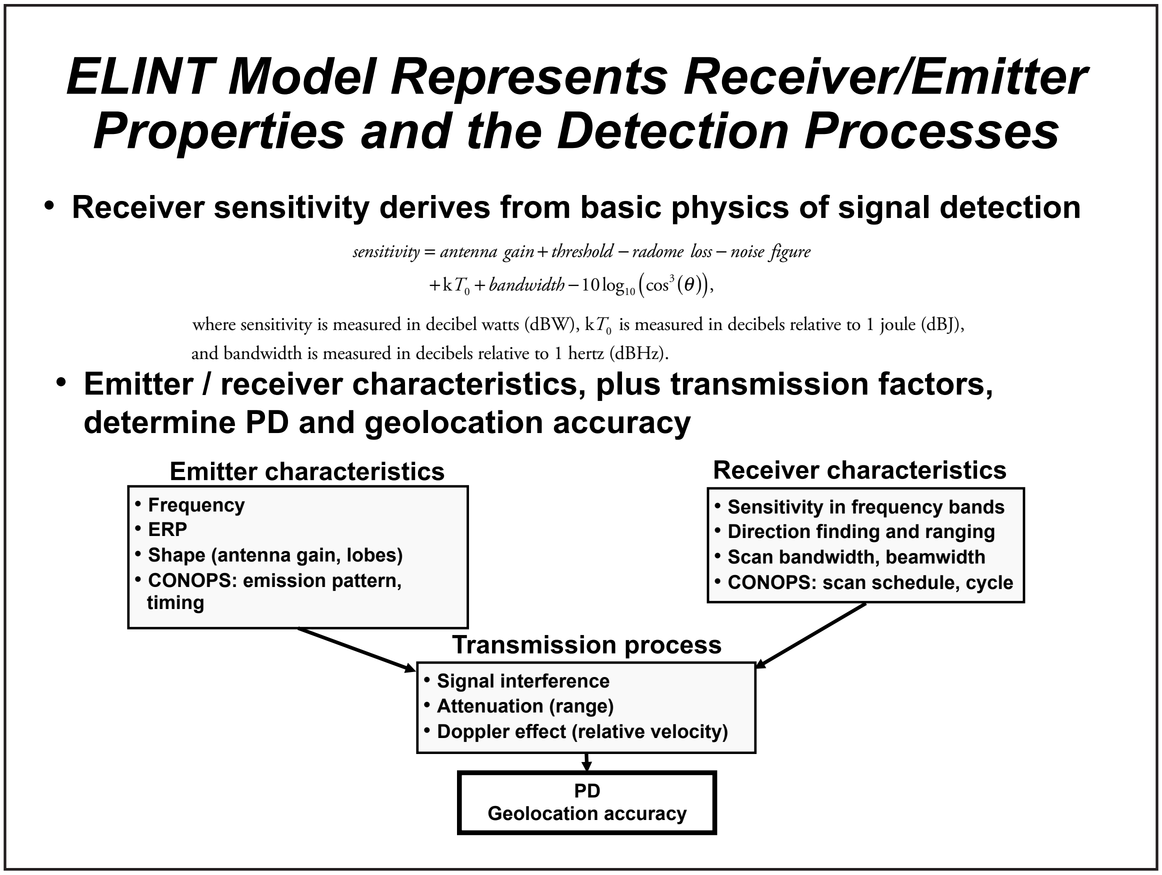
The SAR model predicts detection or classification based on exceeding threshold NIIRS levels. A NIIRS has been adapted for application to SAR images. This measure emphasizes the importance of GSD on image quality. NIIRS is a useful measure because of its familiarity to intelligence analysts but also because performance requirements for sensors are sometimes stated in terms of NIIRS. Although the GIQE is better established for EO/IR than for SAR, Driggers et al. have attempted to calibrate a relationship between SAR NIIRS and IR NIIRS, providing a means for computing SAR NIIRS as a function of GSD (Driggers et al., 2003).

The Driggers et al. model, like NIIRS models for other sensors, does not explicitly capture dependencies on target or environmental parameters, nor details of sensors other than its GSD. For example, it does not take into account the target's aspect to the radar, clutter statistics, or the asymmetry of range/azimuth resolution cells. It does not make a direct connection to detection-theoretic concepts, such as PD and PFA. With some ingenuity, it may be possible for the analyst to account for some of these effects through the degrees of freedom in the GIQE.

Prior to the FY 2010 effort, we modeled SAR NIIRS using expressions calibrated to specific radars, with calibration often over a limited domain of grazing angles. This model did not readily allow generalization to systems other than those for which it was calibrated, and it imposed a sharp cutoff such that SAR provided no useful information at grazing angles below 8 degrees to account for expected degradation in image quality. In the present effort, we developed the SAR NIIRS model for application to radars for which we lack calibration data and implemented a signal model that provides graceful degradation of image quality at low grazing angles, without imposing a somewhat ad hoc and sudden cutoff.

To model radars that lack calibration, we implemented the Driggers et al. expression that relates SAR NIIRS to IR NIIRS. This computation depends mainly on the SAR resolution and does not depend on the other factors in the GIQE that are usually of secondary importance in imaging sensors (such as the RER and height overshoot terms). By replacing the GSD with an "effective resolution" that takes into account target features and viewing geometry, we achieve a graceful degradation in performance at low grazing angles, which we explain in "Additional Detail on Selected Models" at the end of this briefing.

This model was implemented in SCOPEM in the form of a look-up table that gives NIIRS as a function of the radar resolution in the slant plane and grazing angle.



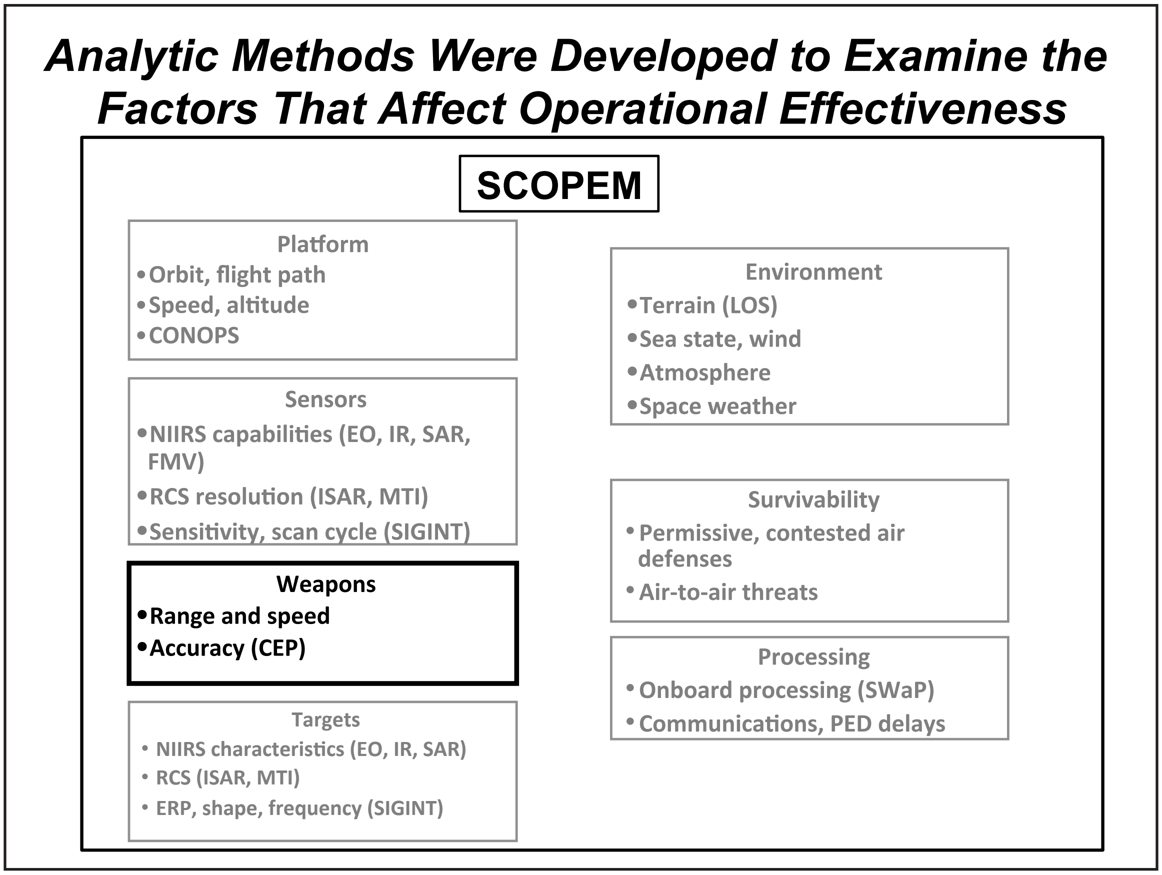
The most complex single module within SCOPEM is the ELINT detection model. In keeping with the broad approach used for other sensor models, we do not simulate details of the propagation of electromagnetic waves. Rather, the model characterizes certain average properties of the target (emitter) and the sensor (receiver)—in this case, frequency and power—to determine the likelihood of detection using standard physics and related environmental factors.

Emitters are characterized by average frequency (middle of band) and effective radiated power (ERP). The ERP is allowed to take different values in different directions to represent main lobes, side lobes, and back lobes. The pattern of emission may be set, and the emitter is allowed to rotate. These characteristics are matched by receiver sensitivity (decibel watt [dBW]) across various frequency bands and signal search patterns, including field of regard, beamwidth, scanning bandwidth, and the scanning cycle—which may emphasize some frequency bands over others. To detect the emitter, the receiver must have sufficient sensitivity and must be looking at the right frequency band (accounting for Doppler shifts), in the right direction, at the right time.

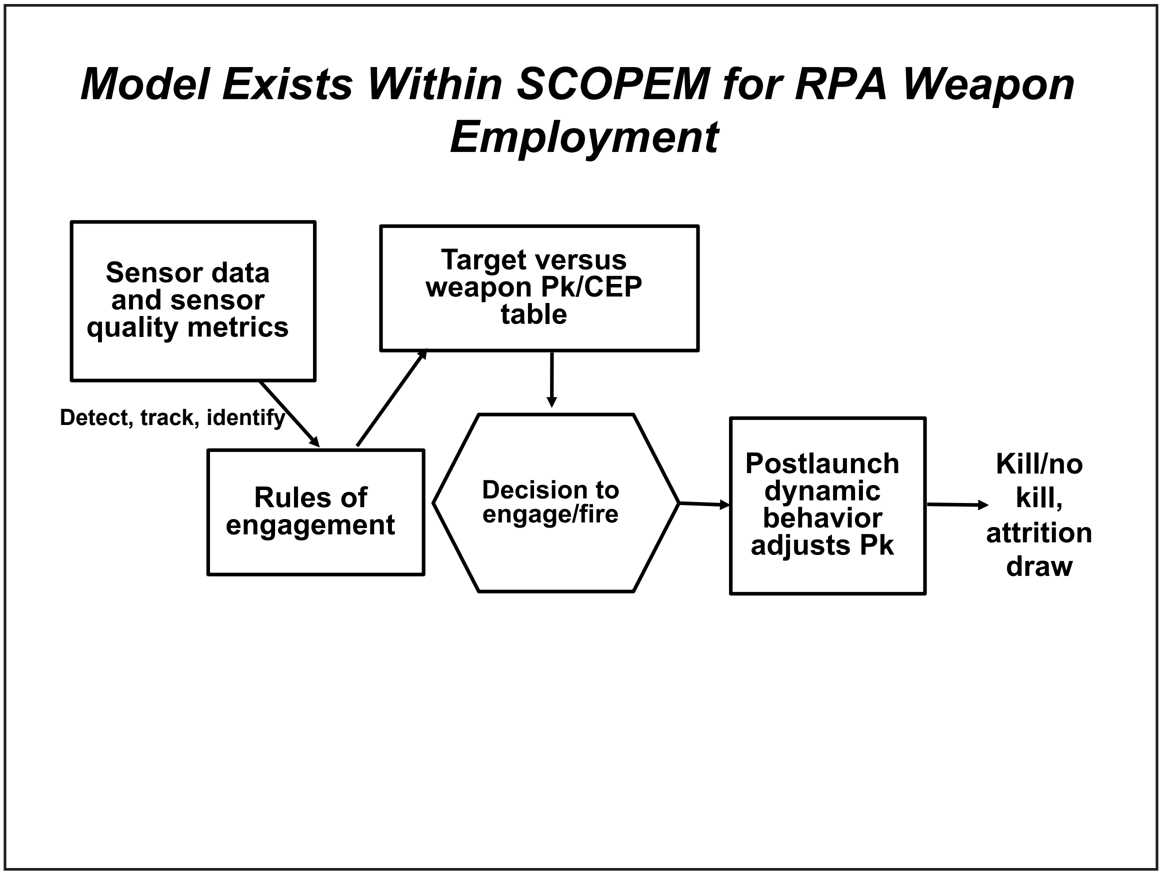
Attenuation of the signal as it travels from the emitter to the receiver is a straightforward function of distance, reflecting the inverse square law. However, other signals at the same frequency may interfere. All signals received on the same frequency at the same time are added (incoherently), and the primary signal must exceed the sum of the others by a given threshold, e.g., 6 dB. Signals may use communications protocols to divide the spectrum by frequency or time; this may be used to prevent interference. Receiver sensitivity also falls off as a function of reception angle relative to the boresight.

The geolocation accuracy of the emitter is determined by direction-finding and ranging capabilities, which may depend on relative angles and the received signal strength. An aircraft may run a line of bases, that is, receive the signal from many points along a flight path in order to triangulate its location more precisely. For simplicity, we use a planar earth for these calculations. Fusing the error ellipses is equivalent to multiplying the Gaussian functions that give rise to them.

With this model, we can represent many of the relevant engineering characteristics of the emitter that are expected to give rise to its performance. We can also represent some simple CONOPS for emitting signals and searching for them. When the factors that give rise to receiver sensitivity, such as the radome loss, are not available, an empirical measure of the sensitivity may be used.



An important factor in assessing candidate RPAs is the employment of weapons, whether by RPAs in a mission or by enemy surface-to-air missiles (SAMs) against RPAs, such as in a denied environment. PAF's approach to address weapon employment leverages existing Air Force and RAND data sources and tools and provides SCOPEM with a means of evaluating weapon effect on mission outcome. The next slide describes our weapon employment analysis.



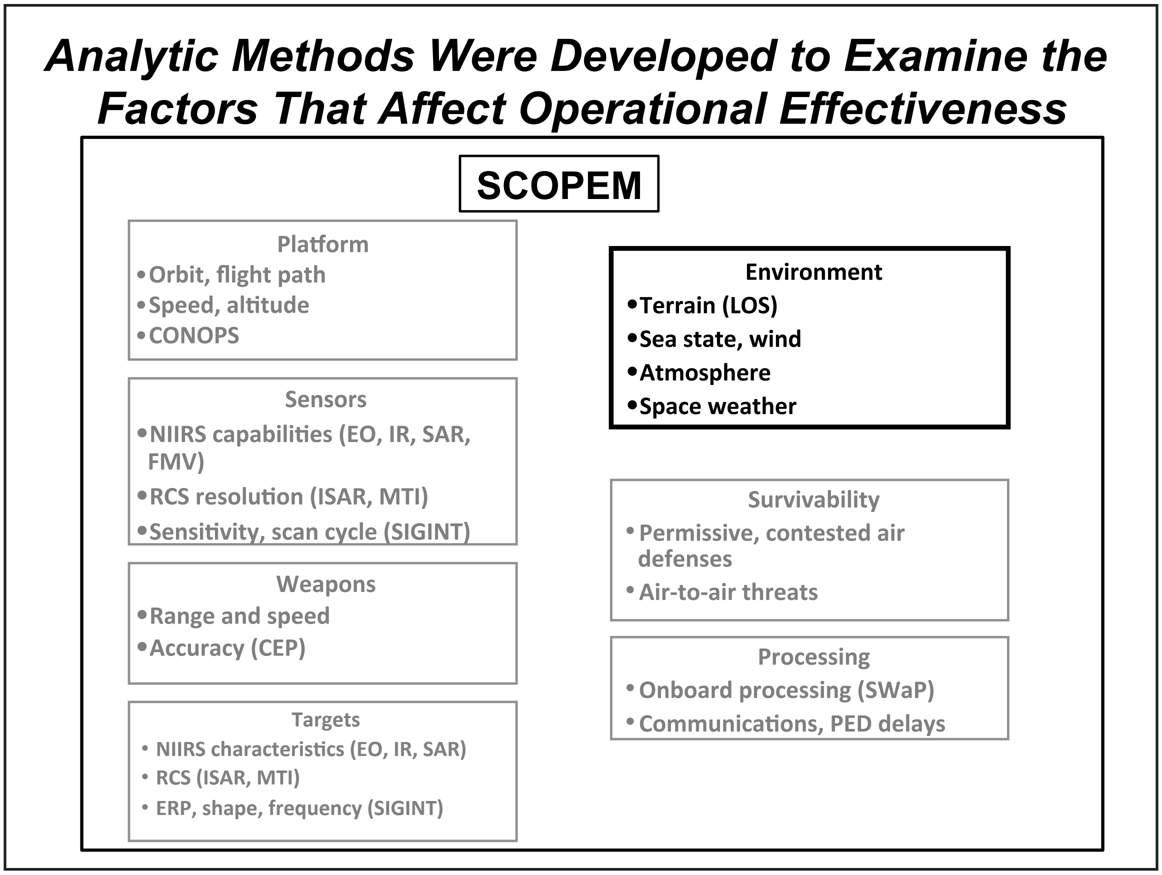
The weapon model in SCOPEM is a natural extension of the sensor model. In order for an engagement to occur, a sensor associated with a given platform must have a track or location and identification of the target (depending on the rules of engagement). Sensors to do this may be carried either by the platform or by the weapon itself. The model is agnostic to what the firing agents or targets are, and it can be employed with a candidate platform, such as an RPA against a fixed ground target or against a mobile SAM. The sensor model outputs whether the sensor was able to provide the necessary information (e.g., NIIRS level to identify the target) in order to engage the target, which is fed into the rules of engagement for any given scenario. If the sensor data are of sufficient quality to justify engagement and the rules of engagement are met, the weapon model then begins an engagement sequence.

Pk and circular error probable (CEP) against particular hardened and nonhardened targets are coded into the weapon model for a variety of weapons from the JMEM data and empirical reports from the Air Force Weapons School.

Provided that the Pk threshold for the particular orientation of the launching platform and target is met, the weapon will fire. Depending on the sensor characteristics of the targeted platform and the time of flight of the weapon, the targeted platform may choose to respond dynamically in a fashion that suppresses this Pk. For example, a SAM can turn its radar off upon detection of a missile fire and thereby dynamically reduce its probability of being killed by antiradiation missiles.

This model can assist mission-level analysis in any vignette in which weapons are employed by an airborne platform, such as close air support (CAS) of ground forces, prosecution of time-

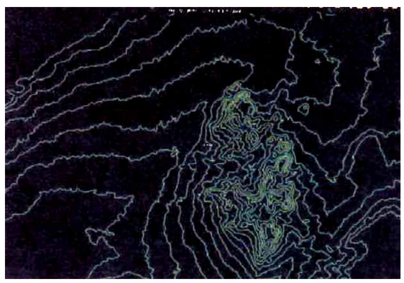
sensitive targets, and in SEAD and DEAD. It can also assist in any vignette that is placed in a contested environment with air-to-ground weapons.



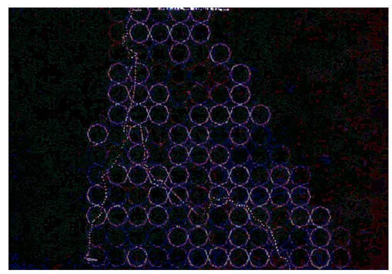
Environmental factors can dramatically change the operational outcome of a vignette for an otherwise successful candidate platform and therefore must be accounted for when evaluating systems at the mission level in SCOPEM. We have developed a suite of methods to address a range of environmental factors. In the following slides, we describe our methodologies for evaluating terrain and LOS, sea state and wind in the maritime domain, atmospheric conditions, and space weather effects on candidate system performance.

Terrain and Cloud Cover Models Determine LOS Based on Altitude

- **DTED and SRTM data provide terrain altitudes**
  - **Draw ridgelines to eclipse visibility (PERL script)**
  - **Set road and location altitudes**
- **AFCCC data provide cloud coverage and altitude**
  - **Set cloud ceiling and percentage of sky obscured (used for random draws at intervals)**



Ridgelines



Cloud Cover

Both terrain and cloud cover can block the LOS between a sensing RPA and the target of interest and must be accounted for in models. Both models rely on large data sets that are available for Air Force research. Digital terrain elevation data (DTED) and shuttle radar topography mission (SRTM) data may be used to establish terrain altitude. Air Force Combat Climatology Center (AFCCC) data are used to estimate the percentage of cloud coverage below a given altitude.

LOSs are not difficult to calculate, but the computation can be time-consuming. Moreover, accurate modeling of LOS requires similarly accurate models of terrain, which can be very challenging to generate, especially in urban environments. For this reason, we represent terrain in two ways. In general terms, we use a practical extraction and reporting language (PERL) script to process DTED at the relevant longitude and latitude to create a set of ridgelines that block LOS. These are also used to determine the altitudes of any locations or roads in the area. The altitudes between the ridgelines are interpolated in a straightforward manner.

For urban environments, however, we adopt a different approach. Rather than modeling individual buildings—which SCOPEM is not well-equipped to handle—we instead represent the relevant roads as "urban canyons" of narrow width and tall walls. This finer representation sits on top of the ridgelines.

Unlike terrain, cloud cover is dynamic. It also has many layers; however, for our purposes, we need only consider the clouds at or below the relevant altitudes of the aircraft. We are not attempting to model weather but to represent the typical effects of weather. Using AFCCC data, we divide the sky into a grid. The percentage of the sky covered by clouds is given for that grid. We initially populate the data by performing a random draw for every area. After a given

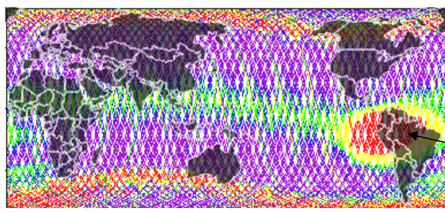
time (usually on the order of an hour or more), we redraw. Critically, we perform a random draw at specified intervals rather than every time because the latter method would permit an aircraft to "see" through the clouds merely by repeated attempts at sensing.

Although the grid spacing and redraw intervals are properly functions of the spatial and temporal coherence of the cloud cover in that area, which could be obtained from the AFCCC data, we use average values for the region and time of year to set these parameters. Higher-resolution modeling of subtle variations in the spacing or interval is not required. Because that would represent a higher level of resolution than is found in the terrain model, it would get lost in the noise. Moreover, because these distributions are not correlated with anything else in the model, repeated redrawing over multiple Monte Carlo runs would be expected to average away these higher-order effects.

Space Weather Model Represents Daily Variation in Transmission Loss Through Ionosphere

- **Defines several shifting regions of signal degradation for several shifting regions of ionospheric activity**
  - **Polar areas (auroral clutter)**
  - **Sun-following regions (scintillation near equator)**
  - **SAA**

- **Used to give dB fade depth (reduction) for transmissions and ELINT detection under "normal" and "severe" space weather conditions**



Space weather must be considered when examining ISR satellites as part of the force structure in theater. Space weather is a large and complicated subject, and we represent only a small slice of it within SCOPEM. Much as we represented only one feature of cloud cover (opacity), we represent one feature of space weather: the fading depth or transmission loss (in dB) through the ionosphere. There are three main geographical regions of concern: the auroral clutter at polar latitudes that affects radar wavelengths, a sun-following region that gives rise to ionospheric scintillation near the equator, and the South Atlantic Anomaly (SAA), which might affect satellite operation.[5]

The theory behind the model is as follows. Roughly speaking, the amplitude of the "noise" in the ionosphere due to solar radiation may be parameterized by the S4 scintillation index. The Nakagami-M distribution links this to the fade depth (dB). That is, for a given S4, we can estimate the percentage of signals we expect to experience at a fade depth of at least a certain level.[6]

Using information provided by the Air Force Research Laboratory (AFRL) Space Weather Center of Excellence, we estimate approximate values of S4 that represent "normal" and "bad" space weather. From this, we use a representative fade depth between the 50th and 90th percentiles, meaning that most of the worst degradation falls into this category. Typical values near the equator might be 3 dB to 10 dB. These fade depths are then used to create

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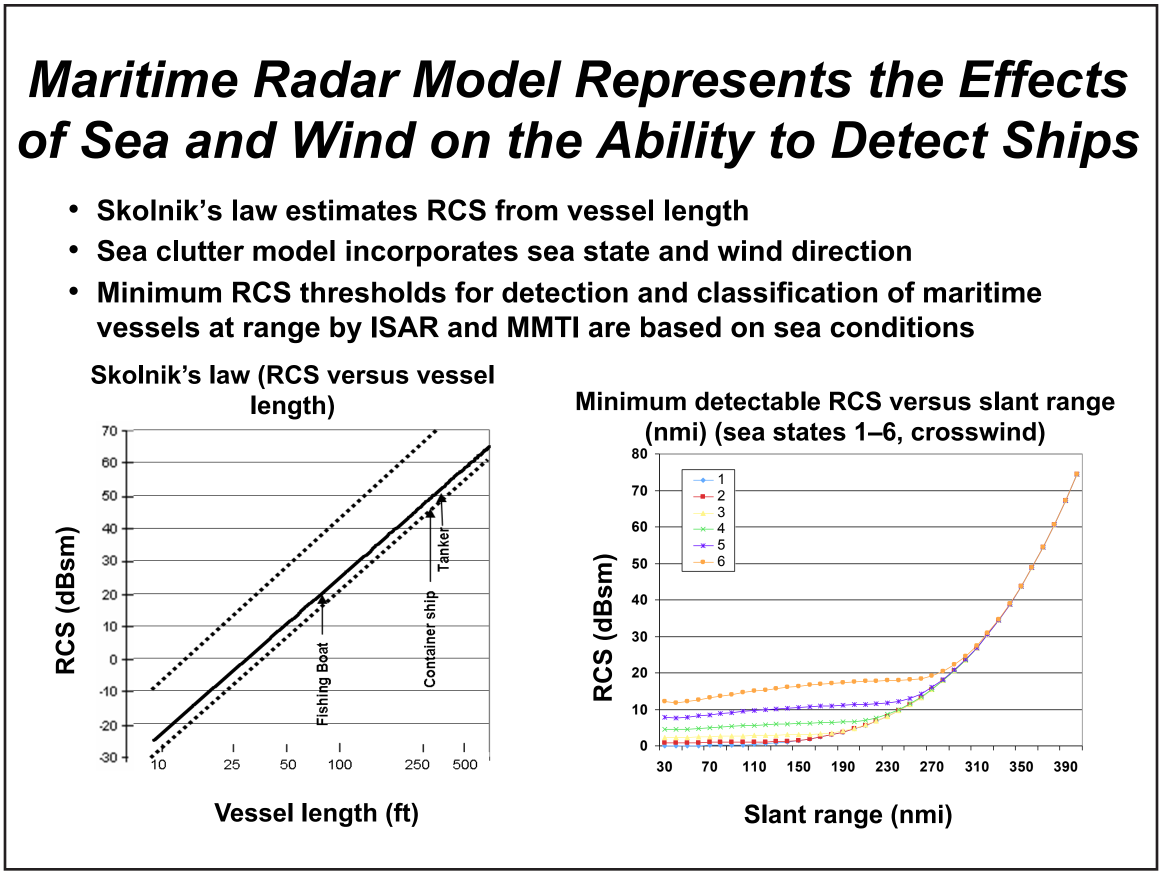
5 *SAA* refers to the area where the earth's inner Van Allen radiation belt is closest to the earth's surface.

6 Nakagami-M distribution is related to the gamma distribution. S4 scintillation index characterizes the severity of amplitude scintillation based on radar track data.

moving regions of signal degradation. At present, the degradation is applied uniformly across the region, although, as the discussion above indicates, a probabilistic model would be marginally more accurate.

The scintillation index is applied very crudely to achieve proper scaling for the effects. We choose this simplistic representation because it is sufficient for our purposes: If space weather is raised as a concern, the concern is likely for the worst-case scenario. There are also other important effects of space weather, such as satellite failures, which we do not represent using these data. Such failures would be modeled instead as either a straightforward blackout or probability. More-advanced use of the fade depth estimates (such as to compute outages) is not warranted by this methodology.



The maritime radar model is used for maritime MTI (MMTI) detection and inverse SAR (ISAR) detection and classification. We describe it in the environmental section here because the wind and associated sea state strongly affect the radar performance. We use the more generalized tracking model described earlier for determining suitable surveillance orbit locations to determine whether targets will remain "in track"—that is, whether the maritime traffic density is such that confusion between ships is unlikely.

In this model, each vessel or target is modeled as having a fixed radar cross-section (RCS) based on its length (in the absence of more-detailed data). An RCS is a fictitious area that represents the strength of the reflection from a sphere with that cross-section. Thus, the RCS may be significantly larger or smaller than the actual cross-sectional area presented by the target. In the case of maritime radar, however, the echoes from a vessel vary considerably from pulse to pulse, so the RCS represents a further level of averaging.

We make several simplifying assumptions regarding target RCS. First, we use the same median RCS for detection regardless of the orientation of the vessel with respect to the radar horn or the height of the vessel. We do so because there is no simple relationship between RCS and orientation or height and, generally speaking, information of greater detail that would permit determination of that relationship is not available. Second, despite the variance of the echo mentioned above, we use the median value, again due to the difficulty of estimating the variance with sufficient precision to merit including it. Third, we ignore the mild frequency dependence of the RCS. Although the order of magnitude remains the same, the equivalent RCS for X-band radar should be somewhat smaller than that for S-band.

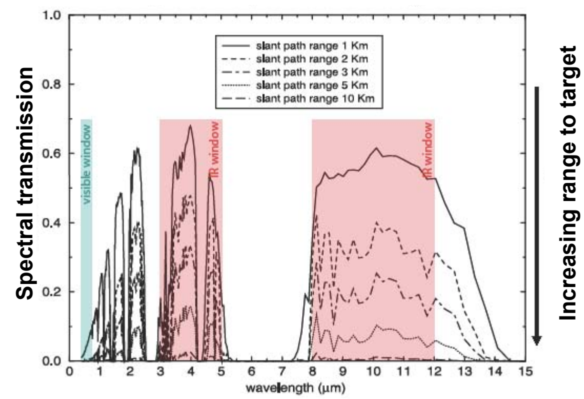
The crucial part of the model is the calculation of the minimum detectable RCS based on sea state and wind direction. Sea state is measured by the international Douglas Sea Scale (World Meteorological Organization, 2006). It is an integer from 0 to 9 that represents the character and height of the waves. Typical sea states for each season are publicly available for most locations; we use National Oceanic and Atmospheric Administration data to set approximate sea regions. The average wind direction and strength are also available. A complex sea clutter model provides different minimum RCS versus slant range curves for each sea state, for both downwind and crosswind conditions (direction relative to the sensor). These curves must be generated separately for each radar.

MODTRAN Is Employed to Model the Effects of Weather on EO/IR Sensor Capability

- **MODTRAN is a Fortran-based program developed by AFRL**
  - **Used to determine the attenuation (transmittance) of EO/IR radiation through the atmosphere for varying weather conditions and climates**
  - **May include various particulates and precipitation: e.g., volcanic ash, snow, fog**
  - **Contains "typical" weather conditions for specific regions at specific times, e.g., "Persian Gulf in August"**
- **Atmospheric transmittance is used to determine NIIRS degradation due to diverse weather and atmospheric conditions**
  - **SCOPEM employs MODTRAN-generated look-up tables to determine the transmittance through the atmosphere for a given look angle, range to target, and sensor type**
  - **The *SNR* term in the GIQE is modified based on this transmittance:**

$$SNR_{fog}\left(R_{slant}\right) = SNR\frac{t_{fog}\left(\lambda, R_{slant}\right)}{t_{standard}},$$

Atmospheric Transmittance Through Fog (visibility 1,220 meters)



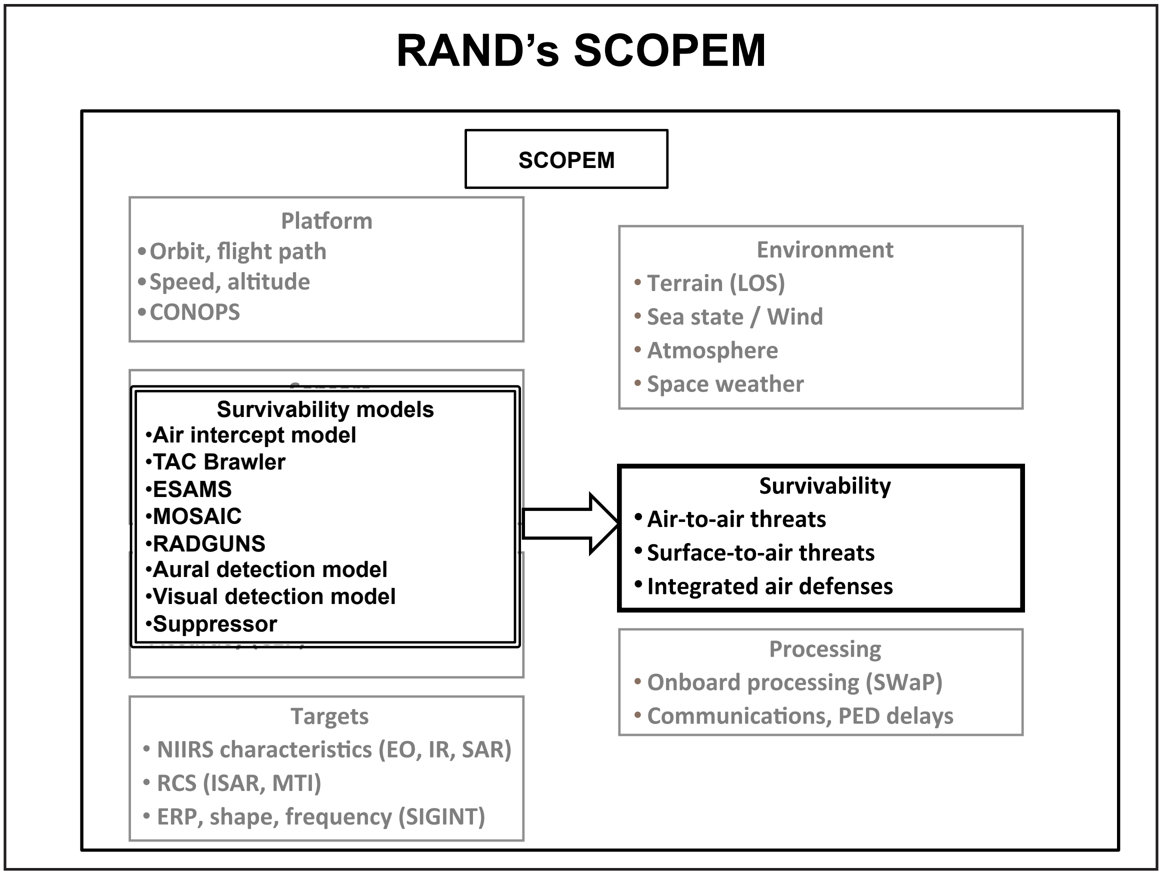
(Mid-latitude, summer and rural aerosols)

MODTRAN is a Fortran-based program developed by the AFRL to determine the transmittance of visible and IR radiation through different atmospheres and weather conditions. MODTRAN has the capability to calculate the effect of particulates and precipitation, including snow, fog, rain, and volcanic ash, on radiation transmittance. An auxiliary graphical user interface, PcModWin, provides access to libraries of "typical" weather conditions for specific regions, at specific times, around the world. MODTRAN calculates the transmittance of radiation at visible and IR wavelengths at different slant ranges and look angles for each weather and atmospheric condition.

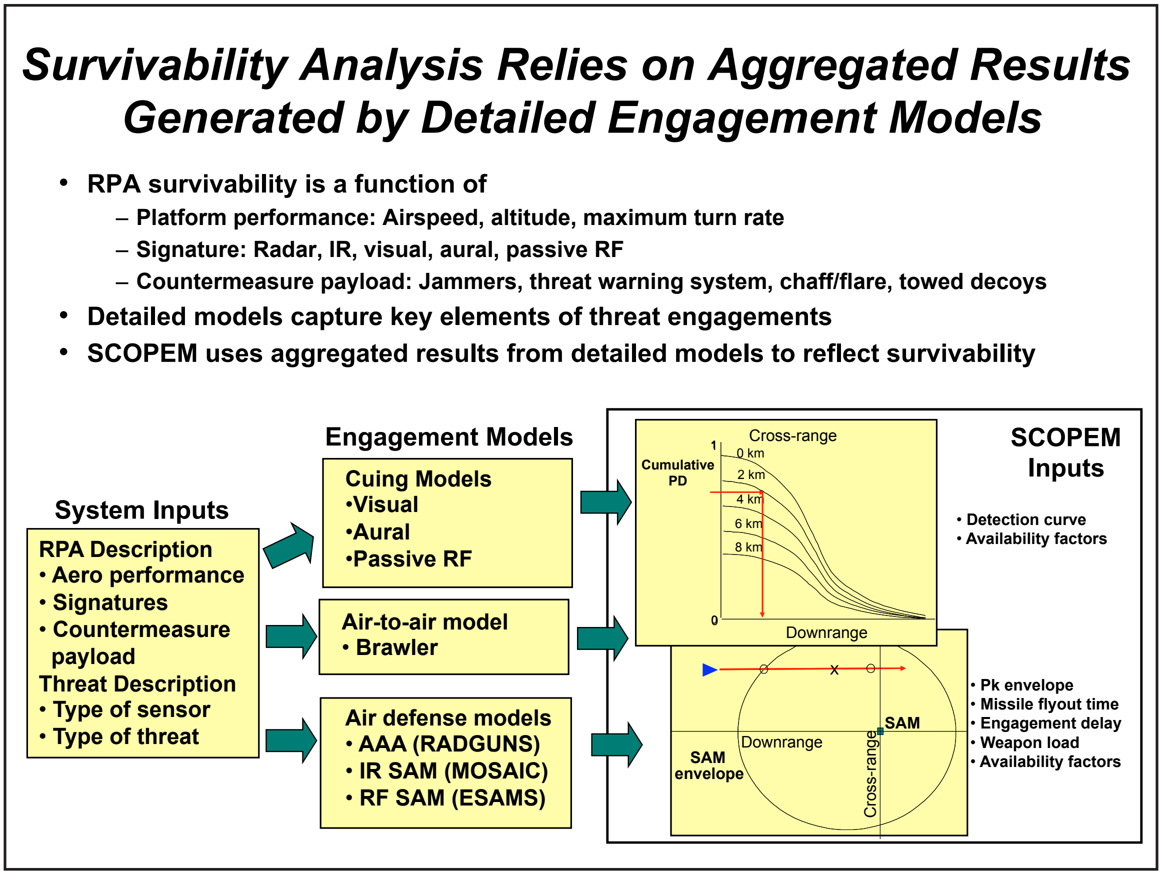
PAF uses MODTRAN (via PcWinMod, versions 4 and 5) to simulate the effects of weather on sensor performance. Specifically, atmospheric transmittance, or attenuation, from MODTRAN is used to determine the associated degradation in attainable sensor NIIRS level in SCOPEM. The average SNR term (as described previously) in the GIQE will be scaled based on reduced transmittance of IR and visible wavelengths through the atmosphere. For example, the scaling factor for a foggy day is determined by dividing the transmittance through fog by the transmittance on a clear day for a given look angle, slant path, and wavelength such that

$$SNR_{fog}\left(R_{slant}\right) = SNR\frac{t_{fog}\left(\lambda, R_{slant}\right)}{t_{standard}},$$

where t_{fog} is transmittance through a defined *radiative fog* atmosphere and t is an average transmittance through a *standard* atmosphere on a clear day.



Candidate platforms operating in contested or denied threat environments may face advanced air defenses, including double-digit SAMs and air-to-air threats. We now discuss the survivability analysis needed for these challenging circumstances and how our survivability analysis provides input into our mission-level model (SCOPEM).



Aircraft survivability is a function of many factors, including characteristics of the aircraft and weapon system, effectiveness of countermeasures, and the CONOPS for achieving mission objectives. Although some models excel at simulating one-on-one engagements with sensors or air defenses, other models excel at capturing overall mission and campaign effectiveness. Models focused on one-on-one engagements typically offer high resolution and high detail but tend to be narrow in scope. By contrast, mission-level and campaign-level models are broader in scope and attempt to capture multiple aircraft and weapon systems in a complex environment.

PAF's approach to survivability analysis involves running multiple high-resolution models that capture the specific factors that determine survivability. The results of these high-resolution models are used for specific point design analyses and translated into formats that can be read by mission-level models, such as SCOPEM, which are less detailed but comprehensive enough to perform mission-level analysis.

To properly analyze survivability, PAF's methodology addresses platform performance, signatures, and potential countermeasures. Platform performance can be described by the altitude, airspeed, and maneuverability (i.e., maximum turn rate) of the aircraft. Signatures include RCS, IR signature, presented area for visible detection, and sound characteristics for aural detection. In the case of RPAs, the characterization of the communication link must also be evaluated because passive radio frequency (RF) sensors may detect the data communications required for controlling the platform and transmitting data. Depending on the space and power available, an aircraft's survivability may be improved by employing a threat warning

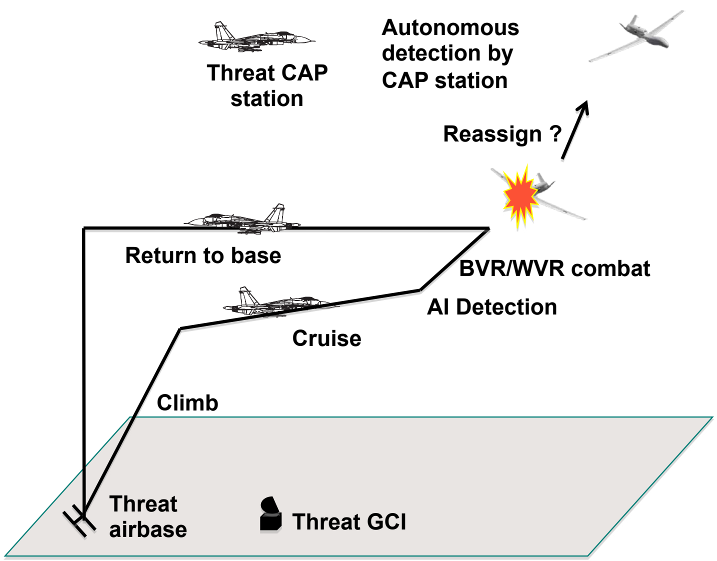
receiver, jammers, flare/chaff dispensers, or towed decoys. PAF has experience with a suite of models and tools designed to address all of these critical survivability characteristics.

The following models are currently available for conducting RPA survivability analysis. We discuss each in the following slides:[7]

- detection engagement modeling
  - aural detection model
  - visual detection model
- air-to-air model
  - Tactical Air Campaign (TAC) Brawler
- air defense engagement
  - ESAMS
  - Modeling System for the Advanced Investigation of Countermeasures (MOSAIC)
  - Radar-Directed Gun Simulation (RADGUNS).

[7] Background on each model is provided in "Additional Detail on Selected Models" at the end of this briefing.

Air Intercept Phases of Conflict



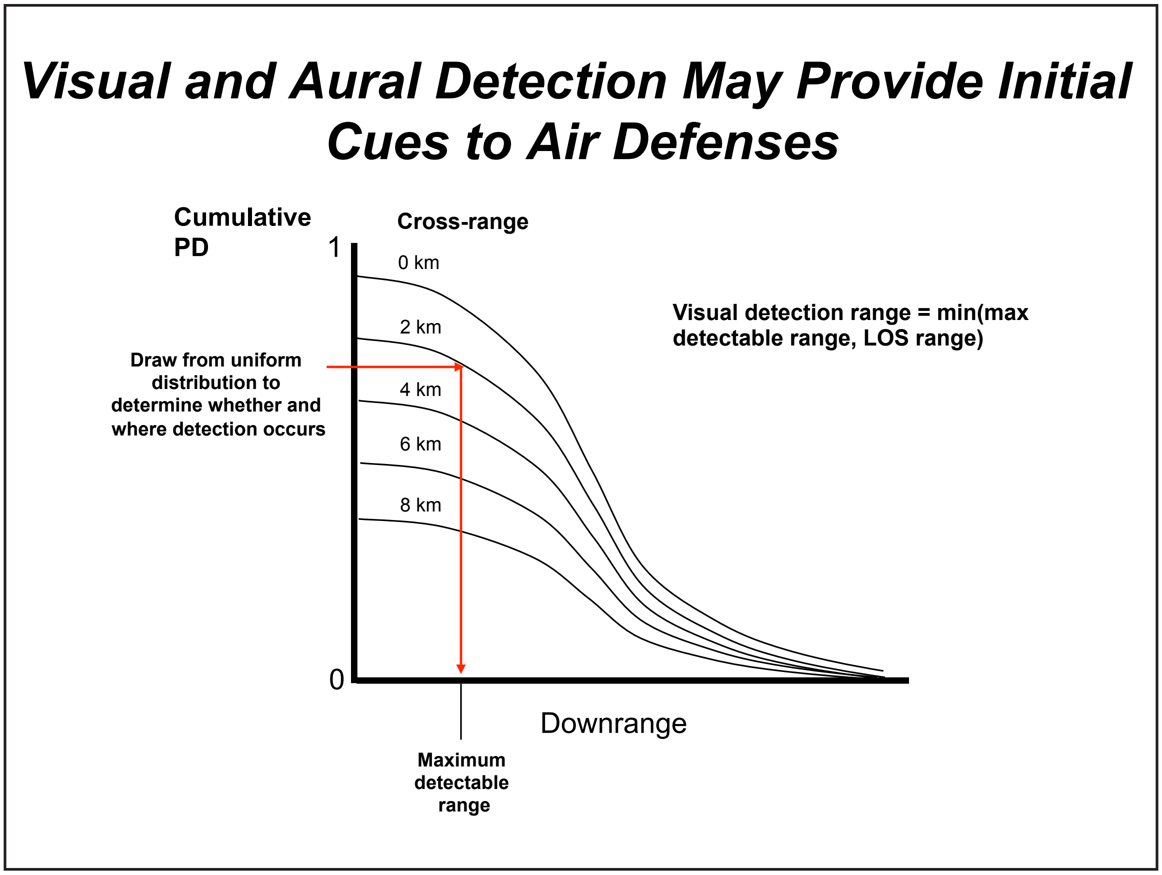
Phase	Phase Title
1	No GCI detection
2	GCI detection
3	GCI track
4	C3 delay
5	Airbase delay
6	Climb
7	Cruise
8	AI detection
9	BVR combat
10	WVR combat
11	Reassign
12	Return to base
13	Maintenance
14	Refuel and rearm

One of the biggest threats to the survival of future RPAs is the air-to-air threat. Threat air-to-air fighters can either be on the ground at an airbase or in the air on combat air patrol (CAP). Shown in this slide is our representation of this threat. The table on the right lists the phases of an air-to-air intercept.

In phase 1, the RPA has not been detected by a ground control intercept (GCI) radar or a threat Airborne Warning and Control System. As soon as a GCI detects the RPA, the intercept goes into phase 2 (GCI detection). The GCI must detect the RPA two times out of three scans before the GCI operator declares a GCI track (phase 3). Once a GCI track has been established, a command, control, and communications (C3) delay begins (phase 4). This delay represents the time it takes from the establishment of a GCI track to the time the sector operations center orders the aircraft to scramble from an airbase. Once the scramble order is received, there is a taxi and takeoff delay (phase 5). The interceptor aircraft then climbs to the cruise altitude (phase 6) and cruises out toward the RPA (phase 7). The airborne radar must detect the RPA two scans out of three to establish a detection (phase 8). If an interceptor is on CAP, it can autonomously detect the RPA and would begin the intercept mission at this point (phase 8). Once the interceptor has established a track, it can employ beyond-visual-range (BVR) missiles and within-visual-range (WVR) missiles (phases 9 and 10, respectively). If the RPA is destroyed, the interceptor can either be vectored toward another RPA (phase 11) or return to base (phase 12), where it can refuel and rearm (phase 14) and possibly conduct another sortie.

The above model is a stand-alone spreadsheet model. Many of the inputs are taken from TAC Brawler. The Air Force model, Brawler, is a high-resolution model that represents air-

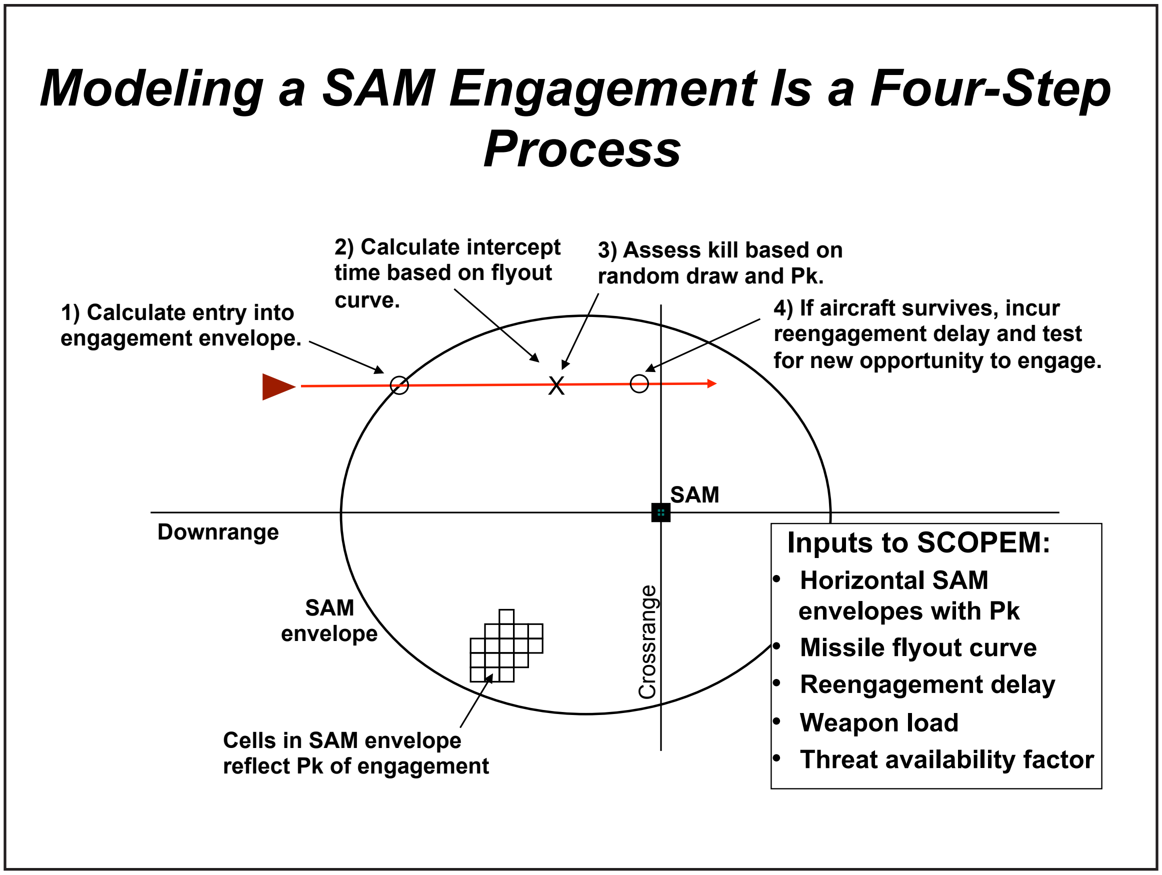
borne threats to blue airplanes. Metrics, such as red/blue kill ratios, are Brawler outputs that feed into SCOPEM as look-up tables.



The visual and aural detection models represent detection by human observers. Although not the primary early detection mechanisms for integrated air defenses with early warning (EW) radars, human observers were used during Operation Allied Force in Serbia. Observers may be cued to the general direction of approaching aircraft, or they may be scanning the horizon for targets. For visual detection, the observer can be aided by optics (e.g., binoculars) or may be reliant on the naked eye. Aural detection may also be treated as aided or unaided, but aircraft engine noise must rise above competing ambient noise levels to have a chance of being heard.

The detailed aural and visual detection models can be used to evaluate the effect of specific RPA platform design choices under varied environmental conditions. Airframe size, shape, and color have a direct impact on visual detection range in our detailed detection model. Similarly, engine choice and placement on an airframe have a direct impact on detection range in our aural model. Environmental conditions, such as haze, cloud cover, foliage, and terrain features, are also captured in the visual and aural detection models. Outputs from these high-resolution models can then be used as inputs into SCOPEM, allowing specific visual and aural detection capabilities to manifest effects on mission-level analysis and trade-offs across CONOPS.

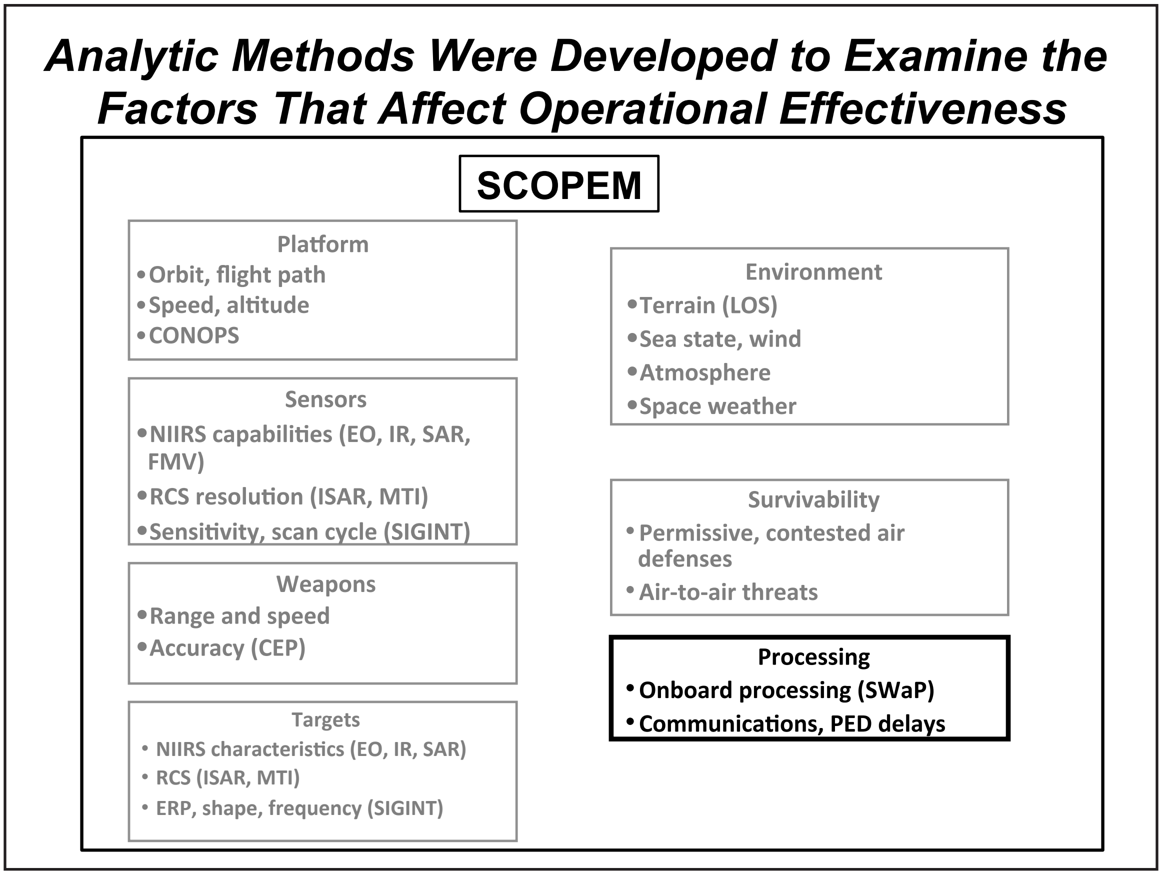
The visual and aural modeling results are translated into SCOPEM inputs through a series of tables containing detection probabilities. By aggregating the results of many runs of the visual and aural detection models, analysts can produce curves describing cumulative PD for various combinations of downrange, cross-range, and altitude. SCOPEM can refer to these detection tables for PD and estimate detection ranges. For points falling between (or beyond) the given set of probability curves, SCOPEM would use interpolation and extrapolation methods to estimate probabilities.



PAF has significant experience modeling air defenses, including EW radars, antiaircraft artillery (AAA), IR SAMs, and RF SAMs. AAA systems are modeled using the RADGUNS model, IR SAMs are modeled using MOSAIC, and RF SAMs are modeled using ESAMS. High-end integrated air defenses with EW and RF SAM radars linked together are modeled using Suppressor. Each of these models is currently in use by the Air Force. Though the format of results from each of these models varies, the results of each model can be translated into a common format that can be interpreted by SCOPEM to represent air defenses. By computing one-on-one engagement outcomes for various combinations of downrange, cross-range, and altitude, each model can produce data sets to build horizontal Pk envelopes. Each Pk envelope is made up of multiple cells, with each cell depicting the Pk of an aircraft at a specific downrange, cross-range, and altitude combination. To implement these envelopes in SCOPEM, additional data are required to supplement the Pk envelopes. SCOPEM also requires missile flyout curves that describe the distance flown for each increment in time, a reengagement delay to reflect the time between shots, a weapon load to establish the weapon system's capacity to fire on aircraft, and an availability factor to reflect the probability that the threat is in use for any particular trial executed in SCOPEM.

To use the Pk envelopes, SCOPEM first calculates the point at which the aircraft enters the Pk envelope. At that point, SCOPEM uses the missile flyout curve to determine an intercept time and location. Using a random draw from 0 to 1, SCOPEM compares the random draw with the Pk reflected in the engagement cell to determine whether the aircraft has been shot down. If the random draw is less than the Pk, the aircraft is presumed killed. If the random draw is higher than the Pk, SCOPEM assesses an engagement delay, then uses the

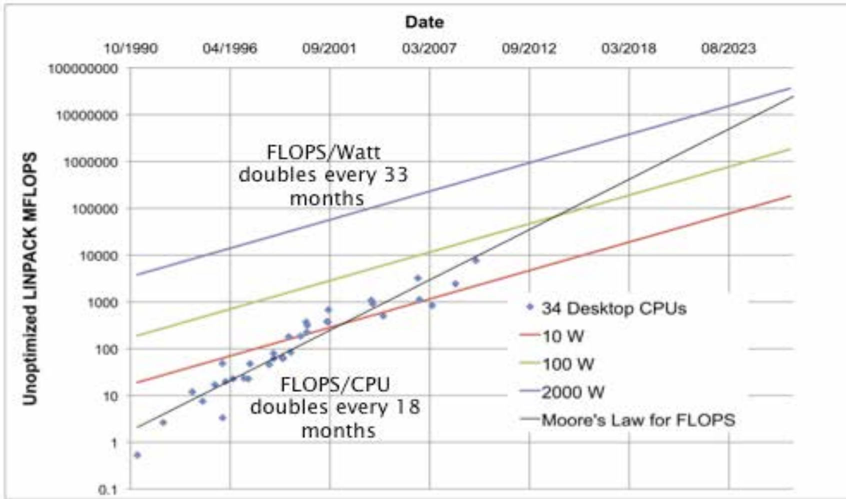
aircraft's updated position to determine whether another engagement is possible. If another engagement is possible, SCOPEM repeats the engagement calculations based on the updated Pk envelope and threat parameters. SCOPEM continues this process until the aircraft is killed, the aircraft leaves the Pk envelope, or the weapon system runs out of weapons.



Conveying data or intelligence between the candidate platform and other platforms or command centers affects the operational effectiveness of the candidate platform. We have developed two tools and leverage a third RAND tool to model these factors. The first evaluates the onboard processing requirements for a mission; the second models the communications network. The third characterizes processing, exploitation, and dissemination (PED) delays for surveillance and reconnaissance data. The first model requires input from SCOPEM. From the mission-level outcome of SCOPEM, the associated data-collection requirement can be fed into our onboard processing tool to evaluate the onboard processing required to implement this candidate in the mission evaluated. The second model also uses data from SCOPEM to evaluate the communications network necessary to employ RPAs in a given mission. The third model provides SCOPEM with a means of capturing the delays associated with sending and processing data. The next three slides describe these tools.

SWaP and Onboard Processing Requirements Constrain Total Sensor Payloads

FLOPS/watts projection through 2025



Analysis of FLOPS for target tracking algorithms 2020

Sensor Type	Kalman Filter GFLOPS	Kalman Filter Power	Bootstrap Particle GFLOPS	Bootstrap Particle Power
Grayscale FMV 5 Hz	50	17 W	50	17 W
Multicolor FMV 5 Hz	450	150 W	150	50 W
Gorgon Stare 12-channel 2 Hz	600	200 W	240	80 W
Gorgon Stare 60-channel 2 Hz	3,000	1 kW	1,200	400 W
200-band hyperspectral 1 Hz	400,000	133 kW	2,000	670 W

Because of bandwidth and personnel head-count constraints to support PED activities, onboard computing is likely to become increasingly important to the effectiveness of sensor exploitation on future candidate RPAs. Computing requirements may scale nonlinearly with respect to sensor resolution and data throughput. Not only has computer chip performance increased exponentially historically, the electrical power consumption of microprocessors has risen as well.

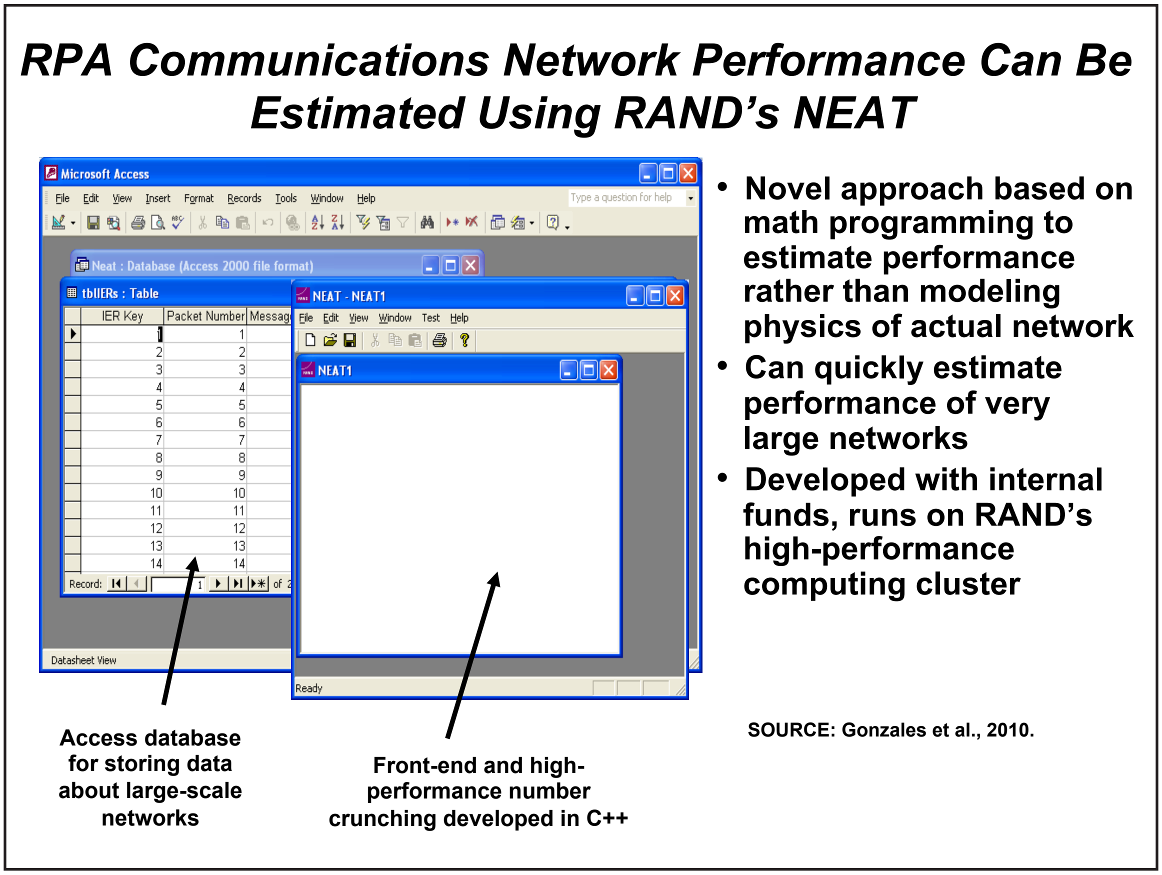
In this slide, we have compiled data on 34 desktop central processing units (CPUs) from 1990 to the present and evaluated how the number of floating-point operations per second (FLOPS) and power consumption per chip have increased over time. Although the number of FLOPS per chip doubles every 18 months in accordance with Moore's law,[8] power consumption increases more slowly, so that the number of FLOPS per watt (W) doubles every 33 months. Because the amount of electrical power on an RPA is likely to be closely related to its total size, available power will eventually become the limiting factor in onboard computing, at which point advances in processing power on RPAs will likely be slower than expected under Moore's law. Plotted on the graph are contours of FLOPS versus time if processing is limited by power levels of 10 W, 100 W, and 2,000 W.

To demonstrate what increased onboard computing power can do in the future, we look at a challenging sensor application that will require or make use of large amounts of onboard computing power: autonomously tracking a target using FMV. We then evaluate the computa-

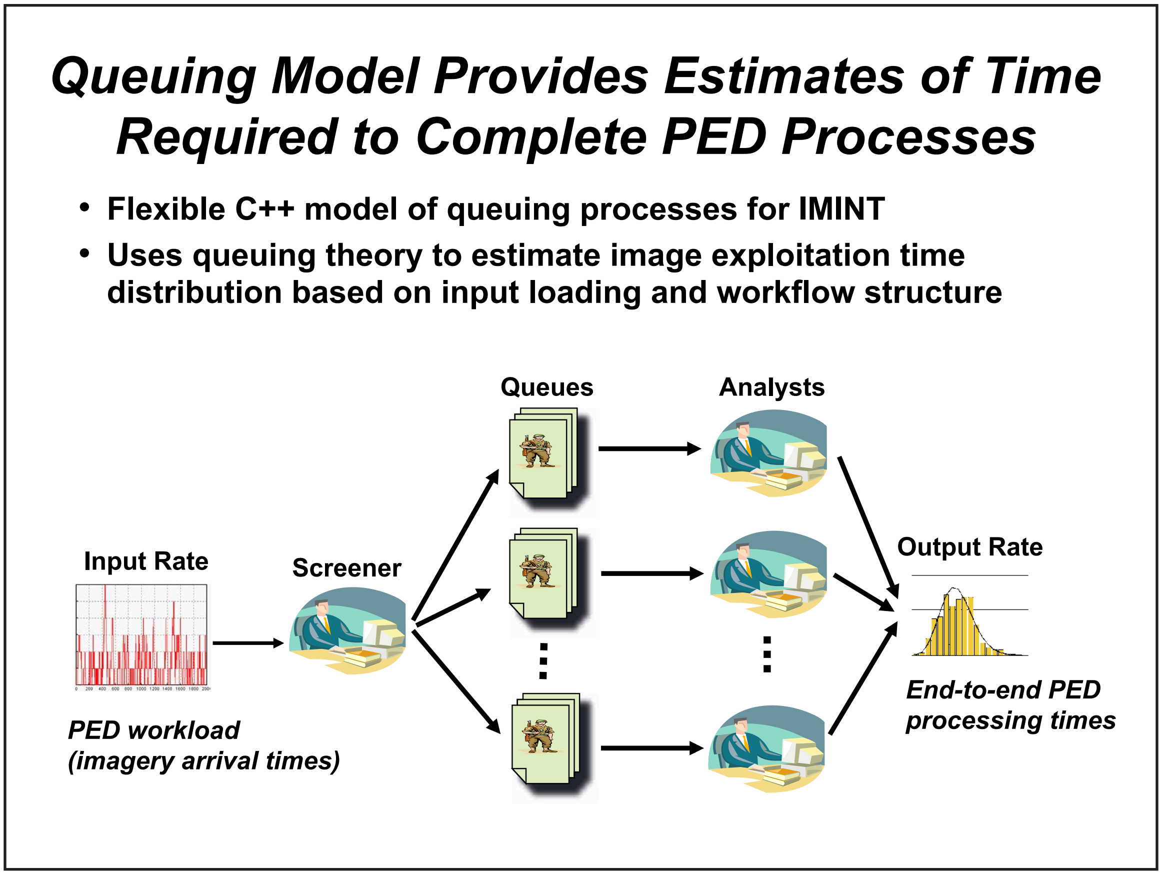
[8] Moore's law states that the number of transistors on a chip will double approximately every two years.

tional requirements for popular algorithms used to address this class of problems and scale the requirements to operationally relevant situations. These requirements can then be converted from FLOPS to watts using historical trend lines from desktop CPUs for a variety of current and future FMV sensors.

As predictions of the future, these estimates are necessarily speculative, but they can give order-of-magnitude projections of which sensor capabilities are feasible for autonomous operation and can have important implications for sensor payloads and processing and communication requirements.



The network exploratory analysis tool (NEAT), which is not part of SCOPEM, is a tool designed to estimate the impacts of architectural changes to network MOPs. MOPs include statistics on throughput rates, packet loss ratios, statistics on message delays, and the number of hops needed to deliver messages. It also enables an analyst to identify key bottlenecks within an architecture where the MOPs are limited. Conventional network modeling tools do this by implementing routing algorithms and simulating the physics of a network, but a drawback of this conventional approach is that simulation run time increases dramatically with the size of the network as measured by the number of nodes and arcs used to represent it. NEAT uses a novel approach that avoids representing the entire network during event-stepped simulation and thereby reduces the computational loading and facilitates rapid simulation of very large networks. The approach is based on a mathematical optimization-based routing scheme that requires representing only a single route during discrete event steps. For more details, see Gonzales et al., 2010.



The PED process is not represented explicitly in SCOPEM but in a separate queuing model. We are interested in the effects of the PED process on the rest of the operations.[9] The primary impact is simply that the PED process requires valuable time, particularly for imagery intelligence (IMINT).[10] The queuing model, programmed in C++, accepts a certain rate of input (incoming images) and returns a distribution of times from which we can draw to determine how long the PED process takes for each image. Alternatively, we can use the average or median time of this distribution.

The queuing model allows us to examine the benefits of different PED organizational structures. In this slide, each analyst is assigned a set of images and works through his or her pile of images separately. A second option would be to use a single queue and allow each analyst to draw the next available image from the list. Targets detected by EO/IR sensors are held onboard the aircraft, or at the ground station, until the PED processing time determined above has elapsed.[11] Then they are released for cuing and further action. This allows us to represent in the larger model the limits this places on Air Force operations. For example, a time-sensitive target that must be identified may no longer be visible by the time the identification is complete.

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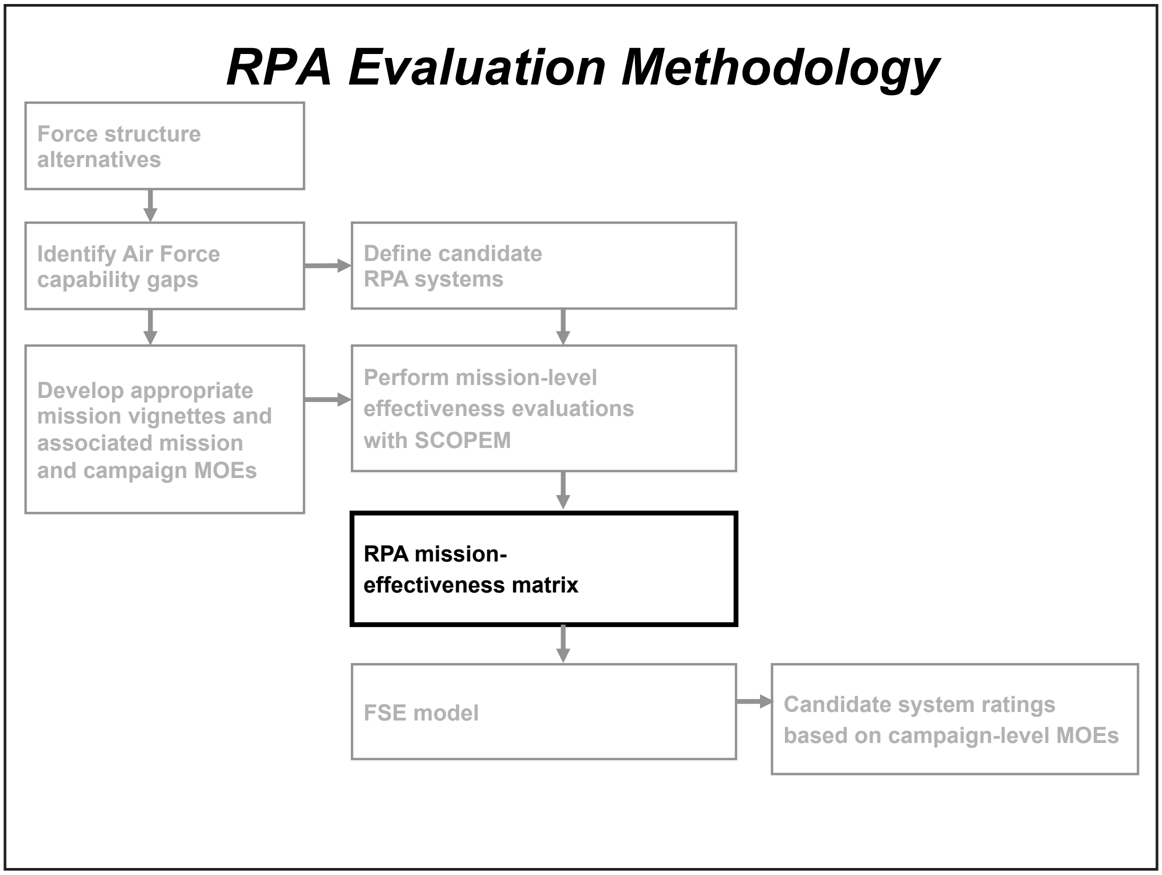
[9] According to recent articles, the manpower for exploitation of a single Predator feed is 19 analysts (e.g., "US Air Force Funds $86M Blue Devil 2 Demonstration Airship," 2011).

[10] SCOPEM can similarly account for additional command and control (C2) or PED delays by implementing a delay in the operational model. Of course, the model is very dependent on the quality of representative data for these delays.

[11] There is no queuing model for other intelligence data, such as SIGINT; for those, we use a single typical time.

By representing the PED process, we can examine the effectiveness of an ISR fleet as a function of the size and organizational structure of the PED enterprise.



Once analysis for a candidate system in a vignette under varying conditions is complete, the effectiveness matrix can be populated. We next discuss the effectiveness matrix by looking at an example.

Effectiveness Matrix Describes Conditions Under Which the System Succeeds

- **Range of environmental factors affect success**
- **Should also note the number of such systems required**

Notional Effectiveness Matrix

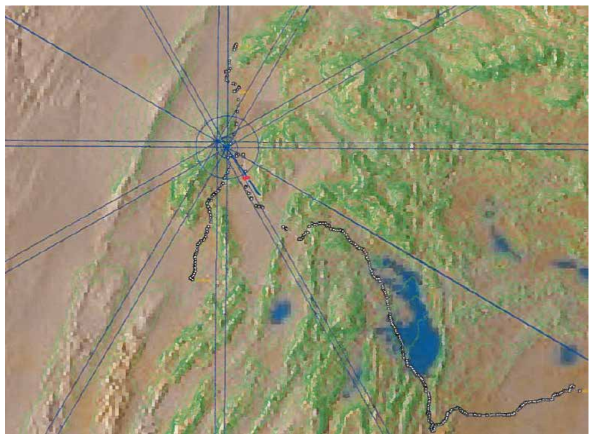
Vignette	Force structure option 1	Force structure option 2	Force structure option 3
1. Overwatch and CAS to defend an outpost	<30 enemies Daylight	Daylight <45 enemies 2+ platforms	No success
2. Detect and track an HVT across mountains and urban terrain	Low traffic <25 km avg.	3+ platforms No confusers	Any nighttime engagement
3. Find and neutralize time-sensitive targets (SEAD/DEAD)	No clouds Daylight only <3 SAMs	Permissive or denied environment	All weather <30 SAMs

The end result of the mission-level analysis should be an effectiveness matrix that lays out the various missions (or vignettes) and describes how well each candidate system performed in that situation or under what conditions the system was able to succeed, including the number of platforms needed and any environmental restrictions (e.g., daytime only).

The effectiveness matrix maps out the trade space to illuminate the strengths and limitations of different system choices. Consider the notional effectiveness matrix shown for the first vignette listed in the slide. Systems 1 and 2 succeed in daylight conditions for providing overwatch and CAS to defend an outpost. System 3 fails. However, SCOPEM analysis shows that system 2 requires two platforms to perform the task, while system 1 requires only one platform. Still, system 2 was more successful at locating and killing enemy combatants (i.e., 45 versus 30 enemy combatants). Thus, the analyst and the decisionmaker see the range of tradeoffs involved in using either system. Ultimately, this kind of analysis would feed into a cost-effectiveness analysis that would compare the relative cost of one system 1 platform with that of the two system 2 platforms needed to succeed in this mission. To understand the number of candidate platforms necessary over a larger campaign, a campaign-level model, such as RAND's FSE, as discussed in subsequent slides, is necessary to establish an overall force structure requirement.

Example Vignette: Track an HVT in Mountainous and Urban Terrain

- **Mission is to track HVT from airport to destination**
  - **HVT leaves airport at some point during 24-hour interval**
  - **HVT may choose one of three destinations randomly**



To illustrate the method in more detail, we ran a test case from beginning to end to compare two notional alternative RPAs in one vignette. The mission was to track an HVT driving from an airport to its final destination. The time of arrival is not precisely known; the vignette assumes that the intelligence specifies only that the HVT is to arrive at some point during a 24-hour interval. Likewise, the destination is unknown. The ultimate mission is to identify the destination by following the HVT.

We considered three different cases of the vignette, corresponding to three different possible destinations. Each case was run 1,000 times to reflect various combinations of environmental factors. We considered clouds, fog, and clear skies; because the airport arrival time is not known, daylight and nighttime conditions were simulated with roughly equal probability as well. The terrain was mountainous, and part of the route went through an urban area, so both aspects of the terrain model were used.

The simulation begins with the RPA circling the airport at a discreet distance, using video surveillance to watch for the HVT to emerge in a vehicle. We assumed that the vehicle was known. The HVT was assumed to travel with the speed of traffic (which varied along the route) to its destination. The CONOPS was that the RPA had to positively identify the HVT vehicle before following it. If the track was lost, the RPA had to repeat the identification process successfully before it could reacquire the track. The RPA was allowed to scan ahead on the highway (in the rural areas) if the track was lost. If the target was never acquired, or the track was lost, the RPA was deemed to have failed the mission. Only if the HVT was tracked all the way to its final destination was it considered a success. The MOE was therefore binary.

Example of Effectiveness Matrix for the "Tracking an HVT" Vignette

Candidate platform characteristics (notional)

	Candidate A	Candidate B
Parameters	25,000 ft, 120 mph	30,000 ft, 300 mph
Sensors	MTS-B, MP-RTIP	MTS-B, Lynx
Weapons	Hellfire	Hellfire, GBU

Percentage of time the platform was able to follow HVT all the way from the airport to the destination (if track is lost or not acquired, mission fails)

	Candidate A	Candidate B
Clear	98%	75%
Cloudy	35%	2%
Fog	0%	0%

Requirement to identify HVT prior to pursuit implies visual image required, hence failure due to weather/fog

The candidate platform characteristics and results of the simulation are shown in this slide. (The speeds and altitudes shown here are approximate.) Both platforms had the same FMV capability but used different GMTI sensors.[12] The weaponry was different but was not used in this particular scenario. In this vignette, the comparative effectiveness of the two platforms was driven by two factors. First, the radar for candidate B was not as powerful, so track was lost more often, even under clear conditions. Second, the requirement to identify the HVT before tracking meant that, if LOS could not be established, as in fog or under clouds, the mission could not succeed.

These results inform the analyst that, under cloudy conditions, neither candidate is particularly effective, while candidate A is preferred over candidate B for following HVTs in clear weather. Adding cost analysis to these results informs decisionmakers on the cost and effectiveness of the two candidates. Inputting these results into a campaign-level model, such as RAND's FSE, will further inform decisionmakers as to the appropriate candidate force size needed.

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[12] The multispectral targeting system for Predator B (MTS-B) is the FMV sensor on board the MQ-9 Reaper. The multiplatform radar technology insertion program (MP-RTIP) is the active electronically scanned aperture radar developed for the Global Hawk Block 40, and Lynx is the radar on board MQ-1 Predator and I-GNAT.

Summary of SCOPEM Environment

- **We model operational effectiveness with a series of vignettes to capture desired capabilities**
- **Measure effectiveness in the vignette; explore variant space**
- **PAF's modeling capability is structured to build rich vignettes out of simple modules of code, to keep it all accessible**
- **Subsystem modeling allows us to evaluate sensor, platform, and environmental factors and provides insight into the mission-level outcomes**

PAF has developed a suite of tools and a mission-level model to examine the operational effectiveness of candidate platforms (e.g., manned and unmanned planes, satellites, and ground-based systems) to perform Air Force missions of interest. We model operational effectiveness with a series of vignettes to capture desired Air Force capabilities. We do this because there is not a one-to-one mapping of capabilities to vignettes. Within each vignette, we explore variations in outcomes based on environmental changes and system modifications (e.g., decreasing the radar signature of the candidate platform).

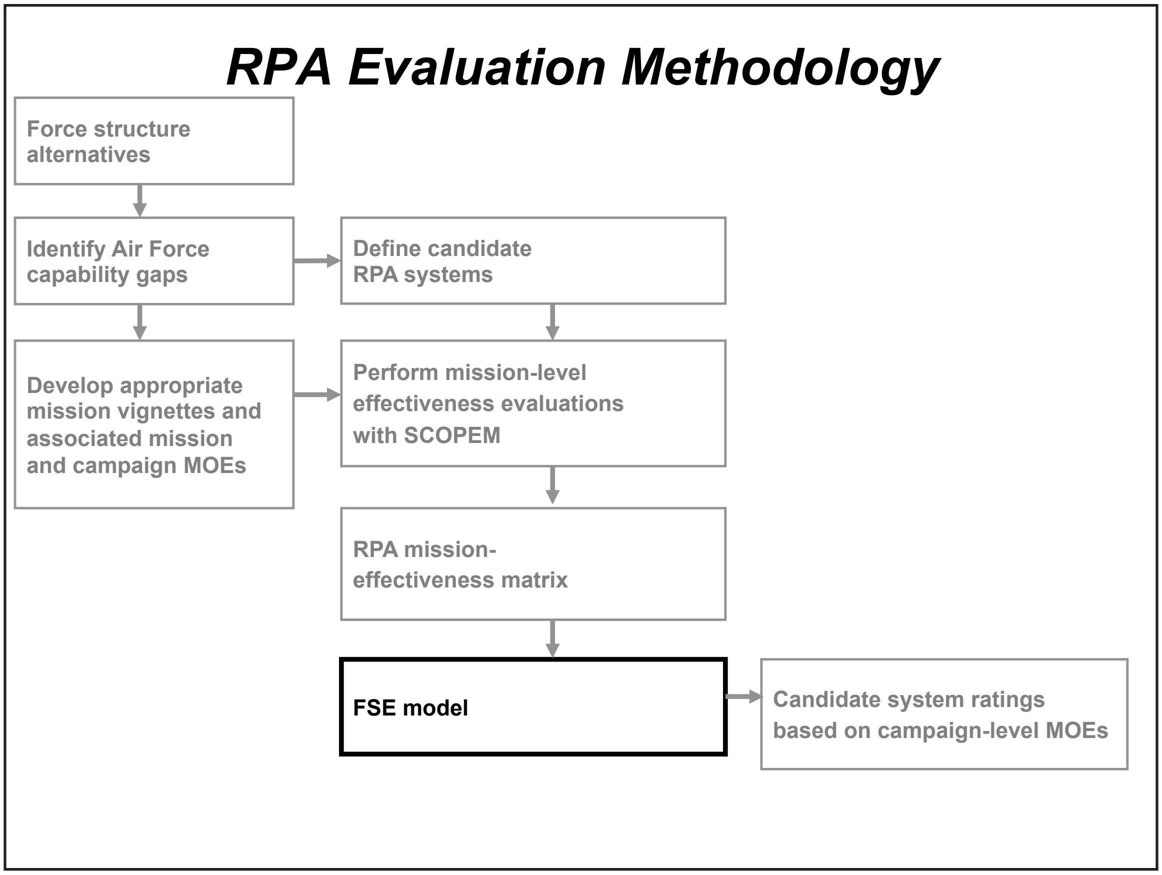
PAF's modeling capability is structured to build a rich vignette with terrain, multiple assets operating together, varied behaviors for platforms, and so on. The modeling occurs in simple modules of code to keep the SCOPEM code accessible. Finally, the subsystem modeling and tools that PAF has developed allow us to evaluate sensor, platform, and environmental factors, whether independently or as inputs to SCOPEM. The subsystem tools also provide insight into the mission-level outcomes. However, mission-level analysis is not enough to inform decisionmakers as to the necessary force structure required of a given candidate. An examination of candidate performance at the campaign level is necessary to recommend the number of RPAs and associated costs of systems for the overall force structure. Before we discuss our campaign-level modeling capability in the next section, we conclude the mission-level discussion with a look at possible additional tools necessary to explore the full range of mission areas for RPAs.

Further Tools Will Be Developed to Meet Analytical Needs

- **Models to analyze near-term sensors could include**
  - directed energy weapons
  - advanced jammers
  - additional nonkinetic attack means
  - LADAR
  - HSI
  - enhanced GMTI model to account for STAP gains
  - geolocation by SIGINT
  - CONOPS for sensor cross-cuing
  - instantaneous data rates
- **Higher-level trade analysis model to explore overall force structure requirements and associated cost**

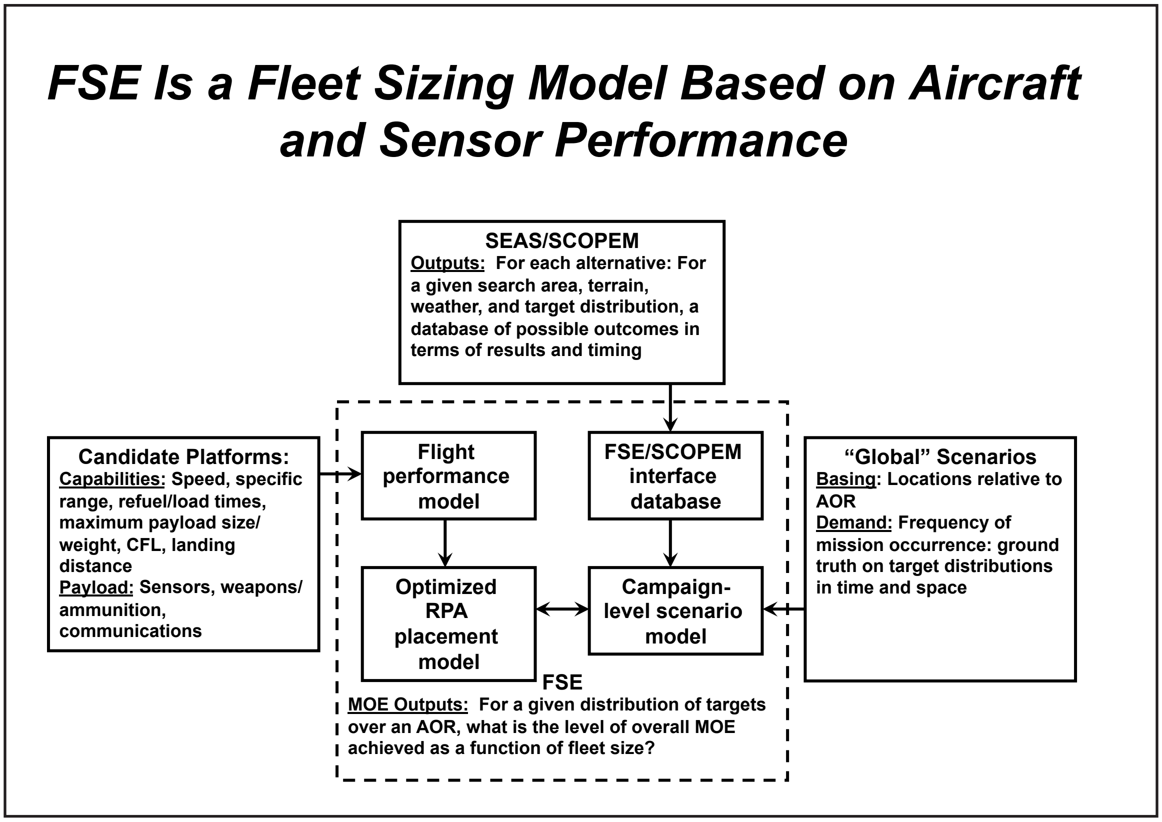
Further tools can be developed to meet the analytical needs of a robust assessment of candidate RPAs in Air Force missions. Models to analyze near-term sensors, for example, may aid evaluation of future mission areas using laser detection and ranging (LADAR), hyperspectral imagery (HSI), space-time adaptive processing (STAP) for GMTI, geolocation by SIGINT, CONOPS development for cross-cuing of sensors, and instantaneous data rates.

Once mission-level analysis is complete, the analyst has an understanding of the type and number of RPAs that are needed to perform a particular mission within a vignette. But, how does this transfer to how many platforms are needed of a given RPA system? A higher-level trade analysis model could be used to explore the overall force structure requirements and associated costs of a given candidate system. PAF has developed a model to aid in this analysis, too.



We now turn our discussion to campaign-level questions and associated analysis that help us determine the necessary force structure to get the job done. For example, we would like to know, for a given distribution of targets over an area of responsibility (AOR), how the fleet size affects warfighting outcomes as defined by a given set of MOEs. MOEs will vary depending on the commander's objectives for the campaign. For nonshooting scenarios, the MOE may be total number of targets imaged. In contrast, for a shooting war, the MOE may be the loss ratio of enemy assets (targets damaged or destroyed) to blue's losses.

We saw in the previous slides that SCOPEM captures the operational effectiveness of a candidate RPA within a specified vignette. The SCOPEM mission-level modeling provides insights into the different capabilities of alternative systems. However, to understand the force structure implications of employing a particular RPA, we need to explore RPA employment at the campaign level. The larger campaign scenario will fold in basing locations of RPA and the frequency with which missions occur (i.e., ground truth on target distributions in time and space). The following slides present PAF's FSE model, which is equipped to help address these issues.



FSE models each RPA alternative as a fleet of RPAs and measures the effectiveness of that fleet against various individual MOEs. FSE includes four primary modeling components: an aircraft flight performance model, a FSE/SCOPEM interface database, a campaign-level scenario model, and an optimized RPA placement model. The overarching objective is to characterize the effectiveness of various aircraft and sensor platforms as a function of fleet size across a theater. This effectiveness measure provides the effectiveness piece of the cost-effectiveness analysis—in other words, the "bang" in "bang for the buck." FSE currently models multiple types of ISR/strike demands, including popup demands, HVT tracking, and combat air support.

The campaign-level scenario model and the optimized RPA placement model run concurrently and draw on the flight performance model and the FSE/SCOPEM interface database. Specifically, both the optimized RPA placement model and the campaign-level scenario model step through time modeling the global scenario and RPA positions and recording the results of RPA engagements. At every time step in the model, each RPA is repositioned based on its speed and direction, and the fuel onboard the RPA is decremented. The speed and fuel burn are driven by the flight performance model, whereas the flight direction is determined by the optimized RPA placement model. The campaign-level scenario model uses the global scenario probabilities to determine whether and where a demand occurs at every time step. The optimized RPA placement model, if RPAs are available, will send RPAs to meet the demand and reposition all other RPAs in anticipation of additional future demands. Once an RPA arrives to fulfill a demand, an appropriate random draw is made from the FSE/SCOPEM interface database to determine the outcome of the RPA fulfilling the demand.

FSE Flight Performance Model Flies RPA Through Each Phase of the Mission

- **RPA characterized by several key inputs**
  - **Weights: OEW, MGTOW, payload, fuel**
  - **Speed envelope: function of weight, altitude**
  - **Altitude envelope: function of weight, speed**
  - **Specific range: function of weight, speed, and altitude**
  - **Takeoff and landing performance: function of weight, field elevation, and field temperature**
- **RPA is modeled through all phases of flight, both in the air and on the ground**
  - **MC rate**
  - **Ground time: load/unload time, refuel time**
  - **Start, taxi, takeoff: time spent and fuel burned**
  - **Climb: time spent and fuel burned**
  - **Cruise/dash: time spent and fuel burned based on specific range and speed**
  - **Approach and land: time spent and fuel burned**

The FSE aircraft flight performance model uses specific range data (distance traveled per unit fuel weight) as a function of RPA weight, altitude, and speed in order to compute fuel burn. The model also incorporates RPA data on maximum speed and altitude capability as a function of weight and altitude, as well as takeoff and landing performance as a function of aircraft weight, airfield elevation, and airfield temperature.

Aircraft endurance, flight envelope, and response time are computed by integrating fuel burn and speed throughout the flight. Each RPA is subject to standard fuel reserve requirements. The FSE flight model accurately allows for the trade-off between speed and endurance to be optimized—for example, the overall FSE model can determine the circumstances under which a high-speed dash is appropriate given that a high-speed dash reduces endurance. The flight model also includes fuel burn during start, taxi, takeoff, climb, approach, and land. In addition to modeling fuel burn, the FSE aircraft flight performance model also computes aircraft ground times and flight times. Specifically, this translates to the percentage of time a single RPA is on station and available to fulfill demands. Finally, the FSE aircraft flight performance model includes details on aircraft takeoff and landing distances as a function of field elevation and temperature. To the extent the RPA is limited by the field conditions, the model will reduce aircraft payload or fuel to accommodate the given field conditions.

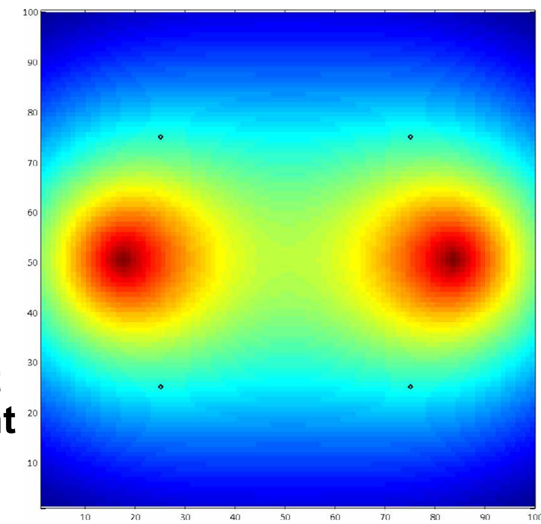
FSE/SCOPEM Interface Database: Integrates SCOPEM Results into Campaign-Level Scenario

- **Sensor performance is modeled through Monte Carlo integration with SCOPEM**
  - **A very large number of SCOPEM runs are recorded in a database, and FSE randomly draws from runs with characteristics similar to those of the campaign-level scenario**
- **FSE matches characteristics between the global scenario and SCOPEM runs**
  - **These characteristics include time of day, weather, terrain, and target type, as well as other scenario-specific characteristics**

The FSE model does not include any inherent sensor modeling. For this, the FSE model relies on an FSE/SCOPEM interface database using a Monte Carlo approach. This database includes a very large number of runs; each run includes information on the conditions under which the run occurred (for example, time of day, weather, terrain, target type) and other parameters. The FSE model, based on the demand defined by the global scenarios, will then randomly draw a SCOPEM run from the database with conditions that match the conditions specified in the global scenario. This random draw is important because SCOPEM data are inherently stochastic because, even with a fixed set of scenario parameters, there is a probability of success. The database pull will then provide the FSE model with information, such as the outcome of the event and the timing of the event. As a simple example, the global scenario may have an HVT cue at an airport and require that the HVT be tracked. If this occurs at noon on a clear day on flat, open terrain, the FSE model would pull an HVT track run from the interface database that also occurred around noon on a clear day on flat, open terrain. This pull would then specify, for example, that the HVT was identified after some minutes of arriving overhead and that the HVT was successfully tracked in a vehicle for a given amount of time before the target was lost. The FSE model would then use the results of this data pull to fly the RPA through the mission and record the outcome for computation of the MOEs. This methodology allows FSE to fully capture the subtleties of sensor performance and stochastics by leveraging the power of SCOPEM.

FSE Campaign-Level Scenario Model: Multiple Scenarios Across a Theater to Compute Fleet Size and Effectiveness

- **A theater is modeled by probabilities of certain events occurring; these events include popup demands, CAS, and HVT tracking**
- **RPAs are continuously repositioning themselves based on changing potentials**
- **Threat probabilities may also be included and aircraft behavior modified to account for additional risk**



The FSE campaign-level scenario is described by probabilities of various events occurring over space and time. The model allows for a ground-truth distribution and an anticipated distribution. In this slide, the color represents the probability of a popup demand occurring. Dark red indicates the areas where popup demands are most likely to occur; dark blue indicates where these demands are least likely to occur. In addition, there are four small black dots, which represent locations where HVT cues may occur.

RPA behavior is modeled using a "potential method." This method uses a potential similar to gravitational potential. In particular, demands are treated as attractive, while the RPAs exert a repulsive force on each other. This means that RPAs will position themselves near areas of high-demand potential, in order to maximize their odds of successfully meeting any demand that occurs, but, because of the mutual repulsive force between them, they will not all cluster in one location. This formulation encourages the RPAs to spread themselves over the battle space. With this potential model, the first RPA will be placed at the point of highest potential; as additional RPAs are added, they will reposition themselves to better cover the battle space while still providing sufficient coverage to the highest-demand regions.[13] The model continuously repositions RPAs; therefore, if an RPA returns to base to refuel, a new RPA arrives, or the RPA is called off to fulfill a demand, all the other RPAs will reposition themselves to again maximize the chance of meeting anticipated future demands.

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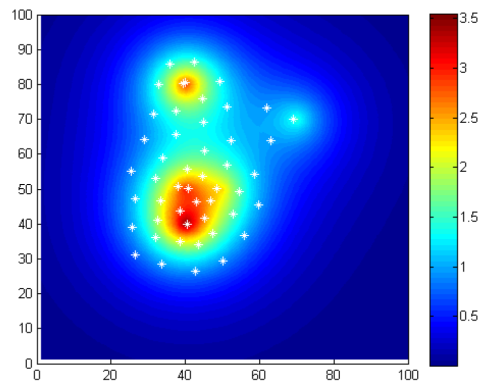
[13] The purpose of a potential model is to simulate the approximate outcome of an intelligent employment scheme without actually having to model artificial intelligence within the program. We do not propose that RPAs would actually distribute themselves via this method, nor that this method would be used to calculate their positions by some central authority.

The potential method has several parameters, which ultimately control the RPA behavior. These parameters are found by performing an optimization[14]—that is to say, the parameters are set in order to maximize the overall MOE. These parameters include the relative attractiveness of various demand types, the distance over which these demands are attractive, and the repulsiveness of the RPAs from each other. As an addition to FSE, the threat environment may be described as a repulsive potential, which would act to push RPAs away from regions of high threat. The amount of repulsion would be an additional parameter used to describe RPA behavior.

[14] A Nelder-Mead search method is used to maximize the MOE and to find the unconstrained parameters. This search method does not rely on local gradients, which is important because the MOE is not a smooth function of the parameters. The lack of smoothness results from the fact that a very small change in the parameters often results in no change to the MOE; when a change does occur, it can be very significant. However, convergence to a global maximum is not guaranteed because the MOE is not a concave function of the parameters. In order to improve confidence, many different starting points are used in the optimization routine.

FSE-Optimized RPA Placement Model: Parameters Depend on the Candidate Platform Characteristics and the Fleet Size

- **Aircraft characteristics, such as speed and sensor performance, will lead to different RPA behaviors**
- **RPA behavior is optimized to net the greatest percentage of weighted demands met**
- **Optimized behavior attracts RPAs to areas of high-demand potential but repels them from one another**



- **Behavior, and ultimately effectiveness, is a function of fleet size**

The FSE-optimized RPA placement model finds the optimum parameters for the potential model, which results in each candidate RPA maximizing its overall MOE. Each candidate platform will have different optimum parameters and will therefore behave differently; however, because of the optimization, each alternative will behave in a way that is similarly optimal. The RPA potential parameters will also depend on fleet size. Small fleets will tend to focus on only the highest-demand regions, and each RPA will position itself far from the others. On the other hand, large fleets will focus on all demand areas, and the RPAs will cluster closer together.

As an example, consider a fast RPA versus a slow RPA. The fast RPA would be able to cover a much larger area in a fixed amount of time than a slow RPA; therefore, the optimization routine would assign a higher repulsiveness to the fast RPAs than the slow ones. This is because slow RPAs have a limited area that they can affect, so they need to be spaced closer together than do fast RPAs. All else being equal, this optimization would lead to the conclusion that a larger number of slow RPAs is required to produce the same level of effectiveness as a smaller number of fast RPAs. This is a critical finding because, once the precise number is computed, it is possible to determine which platform is the most cost-effective. In this example, this would mean determining whether it is more cost-effective to have a large number of slow RPAs or a small number of fast RPAs. If the fast RPA is more expensive than the slow RPA, the answer is not immediately obvious, and FSE would provide the detailed analysis required to address this issue.

The FSE-optimized RPA placement model uses the anticipated demand, which is the estimate of the ground-truth demand from the campaign-level scenario, to position the RPAs in a

fashion that results in them being most likely to fulfill these anticipated demands. Specifically, the optimized parameters will result in the RPAs placing themselves close to regions where demands are anticipated to occur and farther from regions where demands are not anticipated to occur. Given that the anticipated demand is in general different from the ground-truth demand, the RPAs will position themselves to maximize their chance of meeting the anticipated demands, which means that they will not be optimally placed for the actual ground-truth demand. This is correct modeling because the ground truth would, in general, not be known a priori to RPA operators. The distinction between ground-truth demand and anticipated demand is important. For example, to the extent that the ground-truth demand is not known accurately, a fast RPA can more rapidly adjust its position based on actual events.

If a threat environment is included in the global scenario, then the repulsive potential would also be optimized for each RPA platform, such that the optimum balance between threat level and demand level could be found. For example, imagine two scenarios, an area of high-demand potential but medium threat and an area of medium-demand potential but high threat. In this case, FSE may find that the optimum solution is that neither of these areas should be entered, that only the high-demand and medium-threat environment should be entered or both should be entered. In addition, this determination would be a function of fleet size. For very small fleets, FSE optimization would show a risk aversion, but, as the fleet size was increased, this risk aversion would decrease. Furthermore, the platforms' survivability would be crucial in determining the repulsiveness of the threat environment. A highly survivable platform would be less repelled from a threat environment than would a less survivable platform.

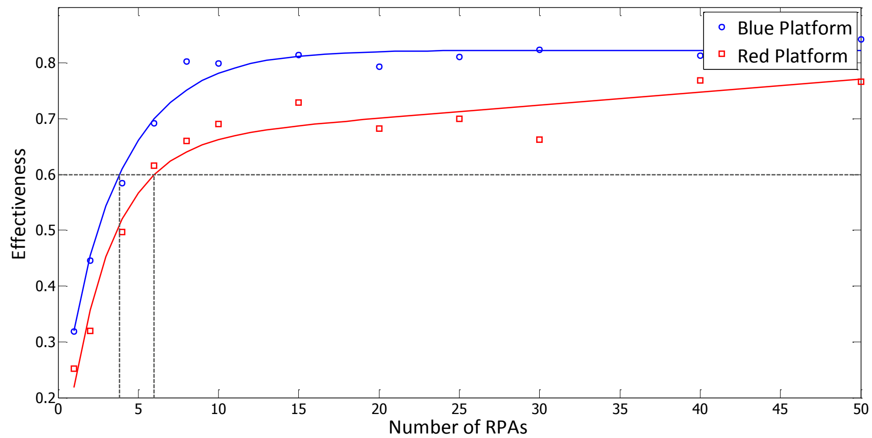
The optimized placement model is a critical component of FSE for several reasons. The model allows for any fleet size to be analyzed. The model allows for RPA alternatives with very different characteristics to be utilized in a manner that maximizes their utility. The model also provides a systematic way to position RPAs when the AOR is larger than can be fully covered by a given fleet of RPAs, i.e., the model is essential when defined orbit locations are not sufficient to meet all demands. Finally, the model allows for dynamic allocation to respond to changes in demand and to changes in the number of RPAs on station.

The slide shows how RPAs would position themselves using the optimization method discussed. Again, the red areas represent regions of high demand, and blue represents regions of low demand. In this image, it is clear that the RPAs are clustering around the high-demand regions but then spacing themselves out over the lower-demand regions. This is exactly the behavior one would expect; specifically, one would want to first fully cover the high-demand regions and then space out the remaining RPAs over the lower-demand regions.

This image does not depict the dynamic nature by which the RPAs are positioned. To illustrate this, imagine that the single RPA placed at the upper red region was called off to fulfill a demand; this would mean that there would be no RPAs immediately nearby to fulfill a possible future demand in the area of that upper red region. Because the RPA that was called off to fulfill a demand would no longer be providing a repulsive force to RPAs around it, there would be a potential gradient moving the nearby RPAs into this gap. As these RPAs move in to fill the gap, they would also be less repulsive to the other RPAs around them, and this effect would cascade as a series of RPAs all repositioned themselves. In effect, the slide shows the steady-state equilibrium for n RPAs. If one RPA is called to fulfill a demand, the remaining RPAs would reposition themselves into the steady-state equilibrium for $n - 1$ RPAs.

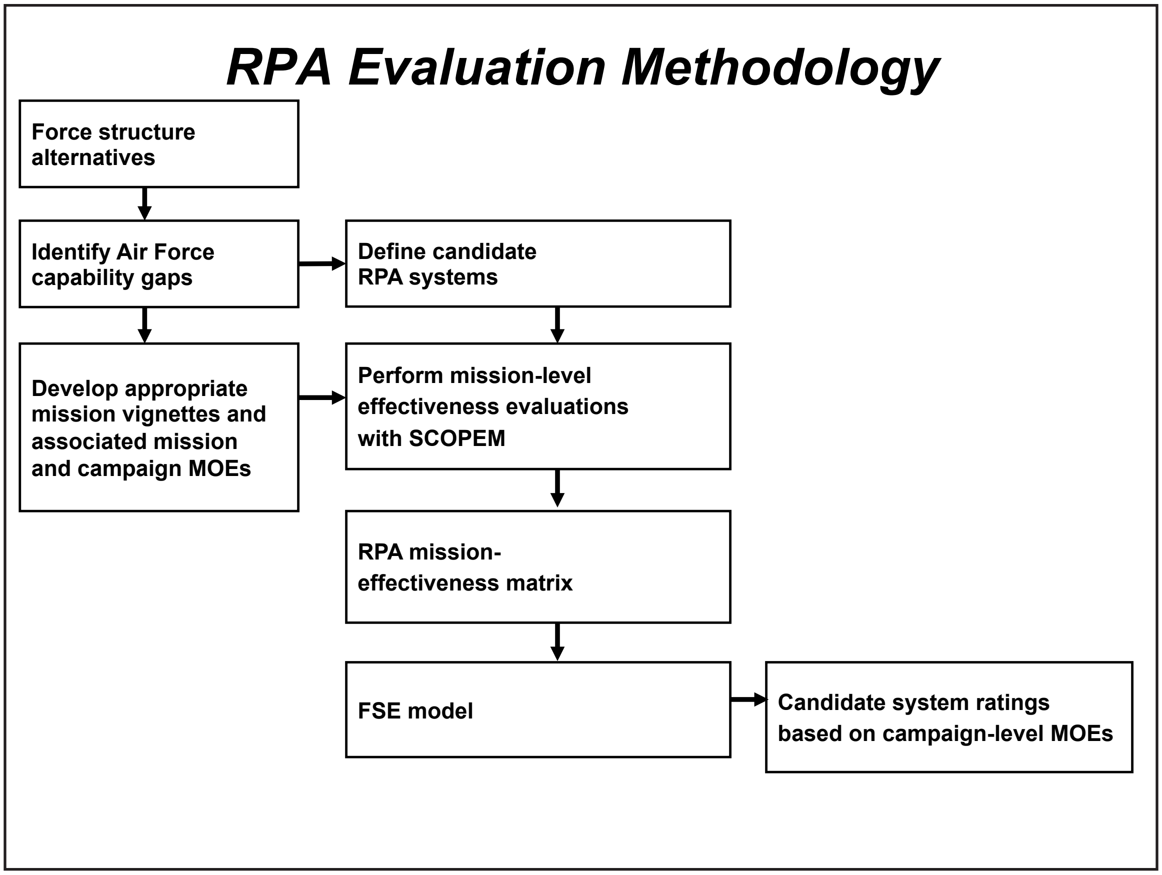
FSE Output: Effectiveness as a Function of Number of RPAs

- **For a given level of effectiveness, the number of RPAs required can be calculated**
- **For a fixed budget (number of RPAs acquired), the effectiveness can be calculated**



A cost-effectiveness analysis can be thought of in one of two ways. First, for a given budget level, what RPA platform will be the most effective? Or second, for a given level of effectiveness, what RPA platform fleet is the cheapest? FSE provides the effectiveness piece of the answer to this question, which can then be combined with cost-estimating to determine the most cost-effective RPA platform. For example, consider the notional chart on this slide. Effectiveness is plotted as a function of number of RPAs. Consistently, the blue platform outperforms the red platform; this means that the blue platform is more effective. The simplest case is that in which the blue RPA is cheaper than the red RPA, which would mean that the blue RPA would be more cost-effective. However, it is often the case that the most effective platform is not the cheapest. When the most effective RPA is not also the cheapest RPA, a full cost-effectiveness calculation is required.

In this case, the relative cost of a blue versus red fleet could be calculated. For illustrative purposes, we will choose a 0.6, or 60-percent effectiveness level. This means that, of all the demands that were simulated, 60 percent of them were successfully fulfilled. Using this effectiveness requirement, the charts show that it would require four blue RPAs or six red RPAs. Therefore, if the relative cost of the blue RPA to red RPA is less than 1.5, the blue RPA would be the most cost-effective; however, if the relative cost of the blue RPA to the red RPA is greater than 1.5, the red RPA would be the most cost-effective.



This documented briefing summarizes models and methods within PAF's toolbox for analyzing many of the factors that affect the operational effectiveness of RPAs and other candidates (including space systems and ground-based assets) under consideration to bridge potential gaps in Air Force capabilities. We presented the individual tools developed at RAND within the past five years, models created in FY 2010 to round out our capabilities, and how existing Air Force models were integrated into our operational effectiveness analysis using SCOPEM and into our force structure effectiveness analysis using FSE.

The suite includes tools to analyze specific aspects of platforms, sensor performance against various targets, weapon effects, environmental factors, platform survivability, weapon employment, computational processing of data, and exploitation of sensor products. These individual tools contribute to the mission-level analysis performed with SCOPEM. SCOPEM is structured to build a rich vignette, including terrain effects, multiple assets operating together, varied behaviors for platforms, and other features that simulate complex operational environments. The modeling occurs in simple modules of code, which provide insight into the factors that drive mission-level outcomes. MOE examples derived from SCOPEM modules include detection of a target for a sensor, LOS obscuration from terrain, and Pk from weapon employment. This level of detail is essential to building an effectiveness matrix, which not only identifies effective platforms and CONOPS but defines the range of conditions under which platforms either succeed or fail at a given mission.

Since it was initiated in 2005, SCOPEM has supported a variety of studies, including the following:

- “Non-Traditional Intelligence, Surveillance, and Reconnaissance” (FY 2008–2009; Jody Jacobs, Bart Bennett; sponsored by USAF/A2)
- “Satisfying the Demand for Surveillance and Reconnaissance in the European and African Theaters” (FY 2008; Carl Rhodes; sponsored by USAF/A2 and USAFE/A2)
- “The Role of Global Hawk in Maritime Surveillance” (FY 2006–2007; Sherrill Lingel, Carl Rhodes; sponsored by PACAF/A2, AF/A2, ACC/A2, and ACC/A8)
- “Tasking and Employing USAF Intelligence, Surveillance, and Reconnaissance Assets to Support Effects-Based Operations” (FY 2005–2006; Sherrill Lingel, Carl Rhodes; sponsored by PACAF/A2).

One must also understand force structure implications of employing a particular RPA. To do so, we explore RPA employment at the campaign level. For example, we would like to know, for a given distribution of targets over an AOR, the effectiveness level as a function of fleet size. A campaign scenario should include mission-level insights, as well as broader considerations, such as basing locations of RPAs and the demand frequency of mission occurrence (i.e., ground truth on target distributions in time and space). PAF has developed the FSE model to perform this campaign analysis. The campaign look afforded by FSE results in a required force size under varying effectiveness levels. The previously mentioned individual tools and the mission-level outcomes from SCOPEM inform the campaign model, FSE. Last, when the force structure evaluation is coupled with cost analysis, a cost-effectiveness examination of the candidate systems is created.

Taken together, this suite of models and tools can help the Air Force explore the most cost-effective ways to take advantage of the unique capabilities of RPAs in the future. PAF is now using the SCOPEM model to study a set of roles and missions for next-generation RPAs.

APPENDIX

Additional Detail on Selected Models

This appendix provides additional details about the radar models (GMTI and SAR), as well as the survivability and air defense engagement models described in the body of the documented briefing.

Additional Radar Details

Ground Moving Target Indicator

GMTI uses two or more pulses to coherently filter out stationary ground clutter, thereby providing detection gain against stationary clutter when targets are moving. In practice, ground clutter is spread out in velocity because of its own motion (e.g., grass moving in the wind) and because of the spread in platform velocity across the beam. Thus, the amount of gain depends on the target's Doppler velocity with respect to the apparent width of the clutter spectrum. If a target is at a velocity that exceeds the spread in clutter velocities, we say that the target is detected in exoclutter—that is, against noise alone. Otherwise, it is detected in endoclutter—that is, against both clutter and noise. To model the endoclutter that limits detection at slow target speeds, we have developed a model that accounts for both the structure of the Doppler filter and the clutter Doppler spectrum. From the radar parameters, we use the radar range equation to compute power received at the radar from a signal and from the clutter at the signal's Doppler velocity. These depend on the signal and clutter RCSs. We have implemented clutter cross-sections for a wide range of environments, from meadows to asphalt, and have parameterized them as a function of grazing angle (Long, 2001). (This grazing angle dependence accounts for the behavior of SCNR on slant range.) SCNR generally will be smallest at very small or very large slant range. This is because, at close slant range, clutter RCS can be very large due to nearly specular backscatter and, at very long slant range, the signal energy becomes small compared to the noise and clutter. Under appropriate simplifying assumptions, PD is related to SCNR and PFA by a simple expression.

As a test of the model, we compared the minimum detectable RCS that we derived with a value reported for the Lynx radar at 25 km at an altitude of 3,048 m (10,000 ft). The Lynx GMTI specification states that it can detect a 3 m-per-second target of 10 dBsm at 25 km in –10 dB clutter ("Lynx," 2009). Our model predicts that the Lynx radar with 32-pulse coherent processing can achieve this performance at platform speeds typical of a Predator MQ-1 and that 128-pulse processing could meet this performance from platforms of much higher speed. (At present, our model does not account for improvements from STAP, which is likely to be

available on any radar that would be fielded on a future RPA that uses active electronically scanned array antennas.)

The GMTI model is implemented in SCOPEM as a table of clutter-to-noise ratio (CNR) values for a range of target Dopplers and platform cross-range speeds. This table is supplemented with target SNR at a set of reference values. The SNR and CNR are readily scaled from the reference values to other sensor altitudes, resolutions, or target RCSs. From these, the SCNR and the resulting PD are easily computed. The CNR table needs to be recomputed for each set of radar parameters.

GMTI modes often are used in conjunction with a tracking algorithm to track moving targets. Although GMTI modes can have good range resolution, they generally have poor cross-range resolution, dictated only by the beam width. Thus, range and cross-range localizations are highly asymmetric, and tracking performance will depend on the direction of the target's velocity with respect to the range direction. In addition to the sensor's ability to localize the target, tracking depends on the potential to confuse the track of one target with another as each target moves between revisits. This potential for track confusion depends on how predictable future target locations are (i.e., on a target motion model) and on the target density.

In tracking algorithms, single or multiple target measurements are used to measure things, such as target position, velocity, or acceleration. These measurements define the "state" vector of the target. Usually, tracking algorithms attempt to predict future state vectors and to combine these predictions with future measurements to arrive at a more accurate determination of actual target location (e.g., the Kalman filter). Future state vectors often are predicted under the assumption that the target is not accelerating. Instead, the possibility that a target accelerates represents a source of uncertainty in the tracking model, and we make this assumption here. It is not our intention to define or model specific algorithms that would be used in a real tracking processor (e.g., Multi-Hypothesis Trackers or probabilistic data association filters) but to capture, in relatively simple terms, nominal performance and explicitly exhibit the dependence on essential sensor parameters, e.g., resolution or revisit rate; on target parameters, e.g., speed, direction, and signal strength; and on environment, e.g., clutter levels and the density of confusion targets.

To accomplish this, we have implemented a tracking model by Mori, Chang, and Chong, 1992, and have focused on results that correspond to a two-element state vector that stores target position. This model is made analytically tractable with the aid of some simplifying assumptions:

- The probability of any measurement can be represented by a multivariate Gaussian distribution.
- Covariance matrices describing measurement uncertainties are the same for all targets.
- The envelope of possible measurements extends far beyond the uncertainty ellipse defined by the covariance matrix.
- Target state vectors are distributed *uniformly* over the measurement envelope.
- When many targets are present within the measurement envelope, the probability of finding even one target within the uncertainty ellipse is small (i.e., targets have low density with respect to measurement accuracy).

As a consequence of these assumptions, the model provides meaningful results only when the probability of maintaining track between revisits is high. Where probabilities become less than 0.5, the assumptions of the model are violated.

We have implemented this model in a form sufficiently general to have potential application to tracking by other sensors as well, although, to date, we have modeled only GMTI tracking using the two-element state vector. The results can be very sensitive to revisit interval, with details depending on the sensor accuracy, motion model, and density of targets. At a sufficiently long revisit interval, the probability of maintaining track will become small as long as more than one target is present and future target positions have uncertainty.

The model has been implemented in SCOPEM as tables of probability of maintaining track for a range of revisit intervals, target orientations, and SCNRs at a set of reference values that includes the target density. Values are readily scaled to different target densities. These tables need to be recomputed for each set of radar specifications. In many cases, for reasons of computational necessity, SCOPEM time steps will be longer than the revisit interval required to maintain track. This is handled easily by scaling the probability for any revisit interval to the SCOPEM time step, and this will yield sensible results as long as such scaling does not require a computation in the regime where the model is inapplicable.

Synthetic Aperture Radar

Our target modeling takes into account how the three-dimensional shape of the target can lead to effective resolutions that differ from the range/cross-range resolution in the slant plane. Three effects are of potential importance. First, at low grazing angles, horizontal surfaces are maximally resolved in range, whereas vertical surfaces are poorly resolved, appearing in only one range bin at the lowest grazing angles. The mean GSD can be obtained by weighting horizontal and vertical surfaces by their respective areas. Second, portions of a target could be in shadow at sufficiently low grazing angles, making less of the well-resolved horizontal surfaces visible. Third, target RCS could be enhanced at low grazing angles that favor specular-like reflections, increasing the relative contribution to total RCS of the poorly resolved vertical surfaces. In particular, the RCS of most targets is dominated by the discrete returns from corners, edges, and interfaces, and we approximate targets as being composed of dihedral and trihedral reflectors that tend to be oriented in the horizontal and vertical directions. Each of these three effects tends to increase the relative importance of vertical surfaces at low grazing angles, resulting in a reduction in effective resolution.

Modeling the first effect of resolution on horizontal versus vertical surfaces is a simple matter of geometry, in which the slant range resolution is projected onto either horizontal or vertical planes. The shadowing effect clearly depends on how target shapes deviate from simple, flat surfaces. For example, a car with a centerline bulge along the length of the roof would have half of its horizontal surfaces in shadow at very low grazing angles. A more complex target, such as a tank, could have even more of its parts in shadow (e.g., by the turret), and shadowing is likely to become a factor at higher grazing angles than for a car (perhaps at angles as high as several tens of degrees). High-fidelity modeling would require computer-aided design representations of vehicles, something far out of scope for this effort. Instead, we adopted a simple model in which the fraction of horizontal surfaces visible is represented by a linear expression with two parameters, the grazing angle at which shadowing begins and the maximum shadowing fraction at 0 degrees. To deal with the third effect of RCS bias, we observe that the monostatic RCS of a trihedral falls off at angles far from its axis, becoming nearly zero at

35 degrees from its axis, but, as angles approach 45 degrees (i.e., either near nadir or 0-degree grazing views), the response peaks again, presumably due to specular reflection from the edges (Sarabandi and Chiu, 1996). We have captured the gross trends of this response in a simple algebraic expression.

We have implemented the SAR NIIRS model that incorporates these three effects and applied them to car-like and tank-like targets. We found that the results are not sensitive to the vehicle dimensions or orientation. It also is evident that the RCS dependence overwhelms the shadowing dependence. Indeed, curves of NIIRS versus grazing angle hardly change if we turn off the shadowing effect. Therefore, we will not use it. The RCS and area weighting of resolution on horizontal and vertical surfaces lead to strong degradation in NIIRS at grazing angles of approximately 8 degrees and less. The example above relates grazing angle to slant range assuming a platform altitude of 40,000 ft and spotlight SAR imagery at 1 m resolution.

Additional Survivability Details

Aural Detection Model

In order to model and evaluate the aural detection properties of various designs, we will utilize a combination of two publicly available noise prediction packages. The first, the Aircraft Noise Prediction Program (ANOPP), is a set of modules developed by the National Aeronautics and Space Administration for input processing, noise prediction, and output noise processing at the observer location. Its purpose is to predict the noise from aircraft, accounting for the effects of the aircraft characteristics—engine, operations, and atmospheric conditions. The second package is called NOISEMAP and consists of a suite of programs that perform noise propagation extrapolation and noise contour calculations. ANOPP will be used to predict initial aircraft noise spectra based on the characteristics of each design. NOISEMAP will then take the predicted spectra and project noise contour maps over a set of standardized scenarios. The results of these scenarios will be compared across aircraft designs to assess aural detectability.

For unmanned aircraft system aural detection assessment, the driving noise factors are characteristics of the propulsion systems rather than airframe noise. The models are quite input intensive, making the detail of the propulsion systems paramount for accurate prediction. Comprehensive information from engine manufacturers, also known as engine decks, as well as detailed characteristics of blade geometry and propeller design, will be necessary to provide accurate inputs for reliable noise prediction. The model does not currently account for the effects of ducting, placement of engines, or airframe noise. The fidelity of the predicted estimates will increase with the introduction of some of these factors and more-detailed input data.

Visual Detection Model

The visual detection model will be used to help determine the probability that the RPA can be detected by either the unaided eye or simple optics (e.g., binoculars). The model takes the parametric description of the airframe and creates a simple three-dimensional model that can be projected on the sky to give effective angular sizes and cross-sections from any distance or viewing angle. It will then use a set of contrast ratios to derive the probability of visual detection at any distance by either the unaided eye or simple optics. The contrast ratio will capture the color-intensity difference between U.S. Air Force gray paint and the sky in a variety of

weather conditions. At higher fidelity, the model will incorporate atmospheric transmission information (provided by an external program, such as MODTRAN) and increased PDs for moving objects in the human visual field.

Because determining the intrinsic contrast ratio from physical first principles is extremely difficult, the fidelity in the model will be dictated by the contrast ratio calibration. The contrast ratio will be calibrated by using data on the maximum visual detection ranges for known aircraft that are most similar to the aircraft being analyzed.

Air Defense Engagement Models

Enhanced Surface-to-Air Missile Simulation

ESAMS is a one-on-one missile engagement-level model that will be used to determine susceptibility to RF SAMs. The model includes aircraft, missile, radar, environment, and electronic countermeasure (ECM) characteristics. ESAMS models the detection, tracking, missile flyout, and intercept, resulting in a Pk against a target aircraft. The summary output includes the initial position from which the missile is launched, the point of closest approach between the missile and aircraft, the miss distance (distance between the missile and aircraft when the missile detonates), and a Pk value.

Missile system data are readily available for most currently existing RF SAM systems. In order to model a SAM system not contained in the standard ESAMS input deck, specific missile system characteristics must be provided. Missile system characteristics include missile fire control, aerodynamics, and guidance of both ground- and missile-seeker radar. ECMs may be also added. Though the model may be run in a deterministic mode, some effects, such as multipath, clutter, and noise, are modeled using ESAMS in a Monte Carlo mode. ESAMS is developed and supported by Survivability/Vulnerability Information Analysis Center.

Modeling System for the Advanced Investigation of Countermeasures

MOSAIC simulates engagements between IR-guided missiles and aircraft with countermeasures. MOSAIC simulates engagements ranging from one-on-one up to few-on-few. Countermeasures in MOSAIC include flares and IR jammers, and both preemptive and reactive countermeasure strategies can be simulated. MOSAIC is capable of simulating laboratory experiments, field tests, and live-fire engagements and is part of the Air Force Standard Analysis Toolkit.

The MOSAIC database includes IR signature data for several types of aircraft, detailed representations of numerous flares and jammers, and high-fidelity models of several types of surface-to-air and air-to-air IR missiles. MOSAIC uses the MODTRAN model to account for the effects of atmospheric absorption and scattering of radiation.

The baseline engagement configuration simulates a one-on-one flyout of an IR missile versus a countermeasure-equipped aircraft flying a user-defined flight profile. The MOSAIC flyout simulation determines the closest approach of the missile to either the geometric centroid of the aircraft or its skin. The primary output of MOSAIC is the "hit" or "miss" determination for a particular engagement. It can also generate time history data pertaining to the aircraft, missile and missile seeker, missile warning system, and countermeasures. The engagement is declared a "hit" or a "miss" according to a user-definable miss distance threshold. Iterating over multiple missile launch points allows for the determination of missile lethal engage-

ment envelopes or "footprints." MOSAIC can also simulate engagements in which multiple missiles of the same type are launched against an aircraft and in which countermeasures may be carried on escort aircraft.

Radar-Directed Gun Simulation

RADGUNS is used to evaluate the effectiveness of air defense artillery (ADA) gun systems against penetrating aerial targets. It can also be used to evaluate the effectiveness of different airborne target characteristics (e.g., RCS, presented vulnerable area, maneuvers, use of ECMs) against a specific ADA system.

The output generated by the program takes three basic forms—tabular data files, data files for plotting, and graphics output files. An engagement simulation produces an event-by-event tabular printout, listing the important results of the simulation. These results include the time, target position, antenna boresight position, rounds fired, single intercept, burst, and cumulative probabilities of hit and kill, expected number of hits, and some user-selectable simulation results, such as target RCS, range of target at time of intercept, miss distance, and tracking errors.

The model is high fidelity, insofar as every round fired is tracked. Also, there are high-resolution models for ECMs, tracking, and other engagement parameters. Up to 30 components of the aircraft can be represented using either a six-view (top, bottom, left, right, front, rear) or 26-view presented vulnerable area, with different areas for four different types of aircraft kills. RCS is defined in terms of the roll, pitch, and yaw of the aircraft, with different tables for differing frequencies and antenna polarizations of the detecting radar. Flight paths can be linear with constant velocity or acceleration over a period of time, nap of the earth, sinusoidal (jinking), a CAS fly-by (with a climb and dive maneuver), with turns or circular paths. Also, terrain can be modeled by adding "hills" that truncate parts of the area from fire. There are also detailed models (firing, detection, and tracking) for each of the ADA systems that are included with RADGUNS. Choices in the weapon system configuration, target and battlefield parameters, and program output are available. Examples are the acquisition radar antenna scan pattern, target track mode, target flight path, clutter and multipath parameters, and various output data options.

Brawler

Brawler is an air-to-air combat model for one-on-one or few-on-few airplane engagements that will be used to evaluate RPA survivability against airborne threats. Brawler is an event-driven, Monte Carlo simulation. Both visual and BVR engagements permit the analyst to represent mission and tactical doctrines, aggressiveness of pilot's actions, perceived capability of the enemy, reaction time, and the quality of the decisions made. Additional inputs include aircraft, weapon, and sensor performance capabilities for the threat and Air Force systems, as well as the force sizes, base locations, and ECM effects.

Useful output from Brawler to reference for SCOPEM input is a log of the scenario modeled that includes important events, such as detections, weapon firings, and kills. A second Brawler output file provides data for statistical calculations in the analysis of multiple runs and would be a source for random draws from SCOPEM given that a similar scenario is explored in the SCOPEM mission-level simulation.

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